ABSTRACT

The captured low-light instrument images suffer from poor visibility caused by low brightness, blurry details, and noise. These images need to be pre-processed to get high-quality images. Low-light image enhancement is about improving the visibility of the low-light image. Previous image enhancement approaches have improved the quality of the low-light image and achieved some results. However, these methods suffer from the problem of heavy computational burden, and the enhanced images have a noise that shows poor visually pleasing results. In this paper, we present a low-light instrument image enhancement approach based on illumination estimation to solve these problems simultaneously. YOLOv4 is used to detect the instrument image, which can reduce time consumption. The detection section is cropped as the input image for enhancing an image. The illumination of each pixel is estimated by finding the maximum value in RGB channels. Moreover, a designed optimization function and Gamma correction are employed to optimize the illumination image as the final illumination image. Finally, a bilateral filter is introduced to remove noise. Experiments on the low-light instrument image are present to demonstrate the effectiveness of the proposed method and its superiority over the state-of-the-art methods.

Keywords: Bilateral filter, Instrument image, Illumination estimation optimization, Low-light image enhancement.

INTRODUCTION

Inspection robots can replace manual to complete the acquisition and reading recognition of substation instrument image. It often occurs in practice that inspection robots capture images in low-light environments such as in dimly lit or indoors. However, the captured instrument images may be disturbed by haze, low light, and other environments. These negative factors will cause the problems of image low visibility, noise interference, which severely limit their applicability. These types of instrument images have a poor visual effect and are not conducive to be used as input for computer visual tasks such as automatic instrument reading recognition and object detection. Therefore, improving effectively the instrument image quality of these images has the significance of the practical application of patrol robots in a substation.

In recent years, various approaches have been presented in the research community to tackle these issues in process of enhancing the low-light images. Early approaches have developed histogram-based methods (Sujee and Padmavathi (2017)) and their variants(Celik and Tjahjadi (2011)). These approaches primarily focus on improving global contrast and enriching image details. However, these methods may not be sufficient to recover local details and brightness of the low-light image. It is difficult to directly reduce or suppress noise during the process of enhancement. Likewise, many subsequent approaches based on Retinex theory are presented to achieve high performance, such as single-scale Retinex (SSR)(Jobson et al. (1997b)) and multi-scale Retinex (MSR)(Jobson et al. (1997a)). However, they focus on recovering the global brightness and contrast of the image without considering the local features and ignoring the effect of noise and artifacts. Although the deep learning-based approaches have improved the quality of an image by employing complex net-works in the case of low-light brightness and noise(Lore et al. (2017);Zhang et al. (2018);Lu et al. (2020)). However, most approaches require a great number of training datasets with ground truth images for training. Their performance is affected by the quality of the training dataset, and images of poor quality in the dataset tend to produce unrealistic results. It is also noted that the existing methods still have their limitations for severely low-light images, while all are relatively time-consuming and suffer from noise amplification.
The following aspects are worth considering for low-light image enhancement: (1) improving the overall and local contrast of the image. (2) To avoid noise in low-light images is amplified while enhancing images. (3) Reducing running time for image enhancement approaches.

In this paper, we present a novel approach for enhancing image brightness and suppressing noise of the low-light instrument images. The image enhancement is regarded as a Retinex-based illumination estimation optimization to acquire a refined illumination image. With the forward estimated illumination image, we use designed an optimization function and Gamma correction for optimizing the forward estimated illumination image. As for the effect of noise, bilateral filtering is employed on the estimated illumination image to suppress noise. Besides, we use an effective image fusion technology to the optimized forward estimated illumination image and the low-light input instrument image to blend the locally best parts in each of the three images into a globally well image. We also prepare a new dataset of 500 instrument images. Our experiments on low-light instrument images show that the proposed approach can improve the enhancement of image brightness and contrast while reducing time-consuming and suppress noise over the state-of-the-art approaches.

RELATED WORK

A great deal of low-light image enhancement approaches has been developed. There are roughly three main categories of approaches for low-light image enhancement, including histogram-based approaches, Retinex-based approaches, and deep learning-based approaches.

HISTOGRAM-BASED APPROACHES

In the traditional methods, histogram equalization is an extensively used method by redistributing the luminous intensity on the histogram for image enhancement due to its simplicity. However, the traditional histogram equalization method may lead to the problem of fewer gray levels or partial details missing after enhancing certain regions. Due to it fails to consider the relationship between pixels. To tackle the problem, many improvement approaches have been proposed by many scholars using additional priors and constraints. Sujee proposed applying a pyramid to histogram matching for enhancing an image, which gives a detailed analysis of enhancing the image and improves the contrasts of the image(Sujee and Padmavathi (2017)). Celik proposed a method that enhances the contrast by using interpixel contextual information(Celik and Tjahjadi (2011)). Ying proposed a novel enhancement method using the response characteristics of cameras, which adjusting each pixel to its desired exposure according to the estimated exposure ratio image(Ying et al. (2017)). Arici proposed a general framework for image contrast enhancement(Arici et al. (2009)). In this framework, contrast enhancement is regarded as an optimization problem to minimize the cost function. Nakai proposed using the differential gray-levels histogram equalization for color images, which contains edge information of differential gray histogram(Nakai et al. (2013)). However, despite these methods are effective in contrast enhancement, they fail to improve the detail and appearance of low-light images.

RETINEX-BASED APPROACHES

Retinex theory assumes that the image consists of a reflective component and a light component(Land (1977)). Therefore, Sethi proposed a Fusion of underwater image enhancement and Restoration method to enhance the contrast of an underwater image(Sethi and Indu (2020)). Fu proposed a weighted variational model, which estimates both reflectance and illumination from a collected image(Fu et al. (2016)). However, it has poor performance in terms of efficiency and visual quality. Guo proposed a structure-aware smoothing model to enhance a low-light image by estimating the light image of an image(Guo et al. (2016)). Wang proposed a method based on frame accumulation and multi-scale Retinex joint processing to strengthen low-illumination images(Wang et al. (2021)). However, most of these methods rely on parameter tuning and do not deal with noise and artifacts well, while large probability estimates are prone to image over-enhancement.

DEEP LEARNING-BASED APPROACHES

Many studies have been developed for handling the problem of low-light images. Chen and Li designed a mask-involved loss function for denoising a convolutional neural network for salt-and-pepper noise(Chen and Li (2019)). Deng introduced an adversarial learning-based model that performs automatic image enhancement(Deng et al. (2018)). Lore proposed a deep autoencoder-based method, which brightens images without over-amplifying the lighter parts in images(Lore et al. (2017)). Gharbi design a new neural network architecture, which learns to make local, global, and content-dependent decisions to press on the desired image(Gharbi et al. (2017)). Wei combine the Retinex theory with Convolutional Neural Network (CNN)(Wei et al. (2018)) and KinD(Zhang et al. (2019b)) to add
a recovery network for denoising noise recovery networks. Yan constructed the semantic map to achieve semantic-aware image enhancement(Yan et al. (2016)). Liu introduced a linear CNN model in deep learning for improving the image(Liu et al. (2018)). It uses the convolution kernel and residual learning to improve enhancement performance. Wang introduce an intermediate in a new neural network to associate the original image with the hoped-for improvement result(Wang et al. (2019)). Chen proposed a new and effective method based on dark pixels prior to realizing the restoration of fuzzy remote sensing images(Chen and Dai (2020)). Besides, for the case of very low light, Chen proposed a new paired dataset and developed a pipeline based on end-to-end training of a fully convolutional network for processing the raw sensor images(Chen et al. (2018)). Dozens of learning-based approaches achieved better results, and learn the mapping relationship from the low-light map to the normal image directly. However, some approach ignores the physical principles of image formation. What is more, some methods do not consider the effect of noise, and thus the image enhancement is ineffective.

**PROPOSED METHODOLOGY**

The framework of the method in this paper is shown in Fig. 1. The instrument in the low-light is detected by using YOLOv4(Bochkovskiy et al. (2020)), and the detection section is cropped as the input image for enhancing an image. Retinex-based, the dual illumination estimation is executed on the instrument image to acquire a forward illumination image(Zhang et al. (2019a)). The low-light region is recovered from the forward illumination image, and the illumination image is optimized with a designed optimization function and Gamma correction. To remove the effect of noise on the desired image, the bilateral filter has been applied to the optimized illumination image by an optimization function and Gamma correction. Finally, the filtered image and the low-light instrument image are fused by using the image fusion technique into the desired image that blends the locally best parts in each of the two images.

**ILLUMINATION ESTIMATION**

The basic assumption of illumination estimation is based on Retinex image enhancement, which supposes that the captured image $x$ can be understood as the product of the desired light-enhanced $x'$ and the illumination image $l$:

$$x = x' \times l,$$

where $\times$ denotes a pixel multiplication. Based on the hypothesis, image enhancement can simplify the problem of light estimation. Hence, it is apparent that only the estimation $l$ is required to recover the desired image $x'$.

To estimate the illumination image of the cropped instrument image $x$. The initial light image $\hat{l}$ is firstly obtained by constraining the illumination at each pixel no less than the value that can just enlarge the maximum RGB color channel. Mathematically, it is expressed as:

$$\hat{l}_p = \max x'_p, \forall e \in \{R, G, B\},$$

where $x'_p$ is a color channel at the pixel $p$. According to $x'_p = x_p \times \hat{l}_p$, to avoid sending RGB color channels of the enhanced image $x'$ out of the color gamut, we employ the maximum values among the RGB color channel as the initial light. Although the initial illumination light briefly describes the overall illumination distribution, it generally incorporates fine-grained textures and details. Therefore, a refined illumination image $l$ is estimated from the illumination image $\hat{l}_p^2$ by dislodging extraneous texture information while retaining the protruding structure. For this purpose, to estimate the ideal illumination image $l$. The following objective function is defined:

$$l = \arg \min_p \sum (l_p - l'_p)^2 + \lambda (w_{x,p}(\partial_x l)^2 + w_{y,p}(\partial_y l)^2)),$$

where $\partial_x$ and $\partial_y$ are the spatial derivatives in $x$ and $y$ directions. $w_{x,p}$ and $w_{y,p}$ are the smoothing weights of the spatial variations. The $(l_p - l'_p)^2$ enforces $l$ to be similar with $\hat{l}'$ at the pixel $p$. The second term aims at dislodging extraneous texture information in $\hat{l}'$ by minimizing the partial derivatives. $\lambda$ is the coefficient to balance the involved two terms. In this paper, the $w_{x,p}$ is defined as:

$$w_{x,p} = \frac{Q_{x,p}}{|(\partial_x \hat{l})_p| + \xi},$$

where $Q_{x,p}$ is the normalized color value at the pixel $p$.
where \( Q_{t,p} \) is inspired by the relative total variation (Xu et al. (2012)), which is written as:

\[
Q_{t,p} = \sum_{q \in \Omega_p} \frac{G_{\psi}(p,q)}{\sum_{q \in \Omega_p} G_{\psi}(p,q)(d,q)_{p} + \xi} 
\]  

(5)

where \( \Omega_p \) denotes a squared window of \( 15 \times 15 \) centered at the pixel \( p \) and \( \xi \) takes a fixed value of \( \xi = 3 \) in Eq.4 and Eq.5. \( \psi \) is the standard deviation which takes the value of 3. \( G_{\psi}(p,q) \) calculate the Gaussian weight based on the spatial affinity between the pixel \( p \) and \( q \), which is defined as:

\[
G_{\psi}(p,q) = \exp\left(-\frac{M(p,q)}{2\psi^2}\right),
\]

(6)

where \( M(p,q) \) denotes the spatial Euclidean distance. In the paper, since the definition of the \( \psi \) is similar with the direction of \( x \), it is not defined.

**Illumination estimation optimization**

To obtain the overall better visual effect and smooth the texture details of the image. Based on the initial illuminated image \( I \), the following optimization problem is proposed:

\[
l = \min((l - l')^2 + \lambda \|W \times \nabla \xi\|_1),
\]

(7)

where \( \| \cdot \| \) and \( W \) designate \( \ell_1 \) norms and Laplace weight matrix, respectively. Further, \( \nabla \xi \) is the first order derivative filter. In Eq.(7), the first term aims to deal with the fidelity of the refined image \( l' \) and the initial illumination image \( I \), and the second term considers the smoothness.

The \( \ell_1 \) norm parametric operation on the initial illumination image \( l \) is somewhat complicated. It is clear that the following relationship is established:

\[
\lim_{\xi \to 0} \sum_{p} \sum_{d \in \{h,v\}} \frac{W_{d,p}(\nabla d p)^2}{\|\nabla d p\| + \xi} = \|W \times \nabla \xi\|_1
\]

(8)

On the above basis, we use \( \sum_{p} \sum_{d \in \{h,v\}} \frac{W_{d,p}(\nabla d p)^2}{\|\nabla d p\| + \xi} \) to approximate \( \|W \times \nabla \xi\|_1 \), and then Eq.(7) can be rewritten as:

\[
l = \min((l - l')^2 + \lambda \sum_{p} \sum_{d \in \{h,v\}} \frac{W_{d,p}(\nabla d p)^2}{\|\nabla d p\| + \xi}),
\]

(9)

when \( \|\nabla d l'\| \) is small, the value \( (\nabla d l) \) is suppressed, the value \( \frac{W_{d,p}(\nabla d p)^2}{\|\nabla d p\| + \xi} \) is also suppressed. Namely, imposing restrictions on the objective \( l \) to prevent generating gradients. Conversely, if \( \|\nabla d l'\| \) is large, the above suppression is weakened, because the location may be on the structure boundary.

As thus, the resulting (9) involves only quadratic terms. The answer is acquired by working out the following:

\[
\hat{l} = l + \sum_{d \in \{h,v\}} D_{d}^{l} \text{Diag}(\hat{\omega}_{d}) D_{d},
\]

(10)

where \( \lambda \) denotes the unit matrix of the same dimension, \( \hat{\omega}_{d} \) is a vector form version of \( \hat{W}_{d}(p) = \frac{W_{d,p}}{\|\nabla d p\| + \xi} \). Further, the operator symbol \( \text{Diag}(\cdot) \) is a diagonal matrix of the same dimension and \((I + \sum_{d \in \{h,v\}} D_{d}^{l} \text{Diag}(\hat{\omega}_{d}) D_{d}) \) is a symmetric positive definite Laplacian matrix.

With a refined illumination image \( l \), it can be recovered by \( x' \times l' \). To recover better brightness and contrast, and the estimated illumination image can be manipulated by Gamma correction, that is, adjusting the \( \gamma \) values (\( l \rightarrow l^\gamma \)) to optimize the estimated light image and recovering the correction results by \( x' = x \times (l')^{-1} \).

**Bilateral filter**

A bilateral filter is a nonlinear filter that considers both pixel point null domain information and pixel range domain information. It uses the null domain matrix and pixel range domain matrix to form a new weight matrix for weighted averaging to suppress noise and preserve edges.

The null domain matrix \( d(i,j,k,t) \) is expressed as:

\[
d(i,j,k,t) = \exp\left(-\frac{(i-k)^2 + (j-t)^2}{2\sigma_d^2}\right),
\]

(11)

where \((i,j), (k,t)\) denotes the coordinate of the center pixel point. \( \sigma_d \) denotes the smoothness of the null domain. The pixel range field matrix \( r(i,j,k,t) \) is defined as:

\[
r(i,j,k,t) = \exp\left(-\frac{\|f(k,t) - f(i,j)\|^2}{2\sigma_u^2}\right)
\]

(12)

where \( \sigma_u \) denotes the difference in the pixel range domain, \( f(k,t), f(i,j) \) denotes pixel values.

The bilateral filtering weight coefficient matrix \( w(i,j,k,t) \) is obtained by multiplying both the null field matrix and the pixel matrix:

\[
w(i,j,k,t) = \exp\left(-\frac{(i-k)^2 + (j-t)^2}{2\sigma_d^2}\right) \\left(\frac{\|f(k,t) - f(i,j)\|^2}{2\sigma_u^2}\right)
\]

(13)
The weighted average is calculated as the filtered pixel value \(g(i,j)\) of the center point coordinates:

\[
g(i,j) = \frac{\sum_{(k,l) \in C} f(i,j) w(i,j,k,l)}{\sum_{(k,l) \in C} w(i,j,k,l)}
\]

(14)

where \(C\) denotes the domain with the center point \((i,j)\) in the range of \((2N+1) \times (2N+1)\). With the control \(\sigma_i\) and \(\sigma_m\) the degree of attenuation, the smoothing of the null domain \(\sigma_i\) is increased to remove more noise from the smoothed area, while the difference of the pixel range domain \(\sigma_m\) is decreased to highlight the edges.

Evaluation metrics

In this paper, we employ three image quality assessment metrics including Peak Signal to Noise Ratio (PSNR), Mean Structural Similarity (MSSIM), and Entropy of Information (EI) for quantitative evaluation.

The PSNR can evaluate the quality of enhanced instrument image, which is defined as:

\[
PSNR = 10 \cdot \log_{10}(\frac{L^2}{MSE}),
\]

(15)

where \(L\) denotes the image grayscale maximum, in general, \(L = 255\). \(MSE\) is mean squared deviation, which is defined as:

\[
MSE = \frac{1}{N \times H} \sum_{i=0}^{H} \sum_{j=0}^{N} (X(i,j) - Y(i,j))^2,
\]

(16)

where \(N, H\) are the row and column of an image, respectively, \((i,j)\) is the coordinate of the pixel point, \(X\) and \(Y\) are the corresponding coordinate pixel values. Larger PSNR values indicate less noise and less distortion in the image, i.e., better enhancement effect and image quality.

The MSSIM is an objective measure for the similarity between the input image and the enhanced one, which is defined as:

\[
MSSIM(S, \hat{S}) = \left( \frac{1}{N_m} \sum_{m=0}^{N_m-1} \frac{(2\mu_{sm} \mu_{\hat{s}m} + c_1)(2\sigma_{sm} \sigma_{\hat{s}m} + c_2)(\sigma_{sm}^2 + c_3)}{(\mu_{sm}^2 + \mu_{\hat{s}m}^2 + c_1)(\sigma_{sm}^2 + \sigma_{\hat{s}m}^2 + c_2)(\mu_{sm}^2 + \sigma_{\hat{s}m}^2 + c_3)} \right)
\]

(17)

where \(m\) denotes the index of the sliding window. \(\mu_{sm}\) and \(\mu_{\hat{s}m}\) represents the means of the input image \(s_m\) and the improved image \(\hat{s}_m\). \(\sigma_{sm}\) and \(\sigma_{\hat{s}m}\) represent the standard deviation. \(\sigma_{sm} \sigma_{\hat{s}m}\) denotes the covariance of \(s_m\) and \(\hat{s}_m\). While \(c_1\), \(c_2\), \(c_3\) are constants to avoid the denominator being zero. Generally speaking, \(c_1 = (K_1 \times L)^2\), \(c_2 = (K_2 \times L)^2\), \(c_3 = c_2/2\), \(K_1 = 0.01\), \(K_2 = 0.03\), \(L = 255\).

MSSIM values are in [0,1], which its larger values indicate higher image similarity and better quality.

EI is a main objective evaluation index to measure the amount of information contained in the image, which is defined as:

\[
H(a) = -\sum_a P(a) \log P(a),
\]

(18)

where \(a\) and \(p(a)\) denotes the grayscale value of the image and the probability, respectively. The larger the EI value, the better the image quality.

EXPERIMENTS

In this section, we present experiments to validate the superiority of the proposed method in this paper and see the effect of the involved parameters. We describe briefly the low light instrument dataset and adopt YOLOv4 to detect instruments. Next, the quantitative evaluation metrics are given. Then, the following four existing image enhancement approaches are conducted for comparisons, including structural weighting strategy (SWS) image enhancement(Guo et al. (2016)), the color correction strategy (CCS) image enhancement(Fu et al. (2017)), the perceptual bi-directional similarity (PBS) image enhancement(Zhang et al. (2018)), and dual-light Estimation (DIE) image enhancement(Zhang et al. (2019a)) method. The experiments are implemented using Python and TensorFlow deep learning framework on the computer with an NVIDIA GeForce GTX850M GPU and Intel (R) Core (TM) i5-4210M CPU.

Parameter setting

The key parameters of the proposed method are \(\lambda\) and \(\gamma\). \(\lambda\) control the smoothness level of the illumination image and \(\gamma\) enhance the brightness of low-light images. Generally, larger \(\lambda\) produce smoother illumination, which is good for enhancing local contrast, while larger \(\gamma\) yields brighter visual results.

Fig. 2 shows an example illustrate the impacts of different \(\lambda\). As shown, larger \(\lambda\) produce smoother illumination, which enhancing the image with stronger local contrast. However, an excessive increase \(\lambda\) will decrease the brightness and contrast.

Fig. 3 shows how the \(\gamma\) value affects the results. As shown, small \(\gamma\) fails to enhance the visibility of the low-light instrument. Increasing \(\gamma\) can enhance the overall brightness, but too larger \(\gamma\) will cause some
details to be lost or blurred appearance. By adjusting the $\gamma$ parameter, we can see that result $\gamma = 0.9$ is satisfactory.

In all experiments in this paper, to recover results with better visual effects, we set $\lambda = 0.6$ and $\gamma = 0.9$.

**Dataset and YOLOv4 instrument detection**

The low light instrument dataset contains 500 images, which are prepared to train and test for YOLOv4. The original images are captured by a high-definition camera in a low-light environment. We adopt YOLOv4 to detect instruments in the low-light instrument image and then cutting the detection section as the input image for enhancing the image. The results of YOLOv4 instrument detection and cropped image as shown in Fig. 4.

**Qualitative Comparison**

We provide a visual comparison to show the overall enhancement effect between the provided method and existing state-of-the-art methods in terms of the cropped low-light instrument images. The comparing results are shown in Fig. 5.

In Fig. 5, the (a) column shows the original low-light instrument image. The (b) column shows the enhancement results of SWS, which can improve the brightness of some images to a certain extent. Although the brightness of some areas is enhanced, the overall brightness is still relatively low. The (c) column shows the enhancement results of CCS, which
enhances the dark parts of the instrument image and increases the clarity of the details in the dials and other places. However, the result of CCS is unrealistic due to many details are still invisible or blurry appearance. The (d) column is the result of PBS, which has effectively restore the brightness. However, the noise is amplified on the dial, and some of them are prone to over-enhancement, which can easily lead to the problem of loss of texture and detail information. Similar to (b), the (e) column is the result of DIE, which cannot recover all hidden details from the low-light images while the phenomenon of noise being amplified appears. The (f) column is the result of the proposed method. The image of overall brightness, the image detail information, and contrast are enhanced. Besides, the results of the image appear more natural while the noise being amplified is suppressed.

In contrast, the proposed method in this paper is more consistent with human understanding of images in terms of subjective evaluation of image brightness, contrast, and sharpness enhancement, and obtain high-quality visual effects.

A grayscale histogram reflects the frequency of grayscale values in the image. The horizontal axis from left to right represents the shading from black to white. Thus, the data in the grayscale histogram of a low-light image is mostly concentrated on the left side, while the opposite is an overall brighter image. The more balanced the distribution of pixel intensities on the 0–255 grayscale, the better the contrast of the image. Fig. 6 shows the histogram distribution of the enhanced low-light instrument image.

Fig. 6. (a) shows the histogram distribution of the low-light instrument image. The dynamic range is narrow and concentrated in the low gray area due to the darkness in the low light instrument image. As shown in (b), the dynamic range is somewhat stretched, but the effect is limited. In (c), the image is enhanced to some extent in the overall range, however, the gray level range is narrow and concentrated around the gray value of 50, which indicates that the enhancement effect is poor. In (b), there is more evenly distributed in the dynamic range, however, the proportion of some high brightness areas is higher, which indicates the phenomenon of over-enhancement. For (e), DIE makes the dynamic range is somewhat stretched, but most of them are still in the low gray range, and the maximum gray value is around 120. In (f), we can see that it occupies most of the dynamic range of image gray value in the histogram and increases the dynamic range. At the same time, the gray value is distributed around 150, which shows that the method can expand the image gray value distribution and enhance the image brightness and contrast.

Quantitative Comparison

In addition, this paper also compares various image enhancement methods using the three objective evaluation metrics introduced in Sec.4.1.

In general, higher PSNR and MSSIM mean that visibility is better enhanced. While higher EI means that details are better preserved. Table.1 shows the average values of the objective metrics obtained from the enhancement of six random instrument images.

As shown in Table 1, we can see that our method significantly outperforms better compared to the existing methods in terms of all three metrics. As shown, the proposed method not only improves brightness and preserves rich detail information of the instrument images but also removes the noise and improves the overall quality of the instrument images.

Table 1. Comparison of PSNR, MSSIM, and EI metrics of different methods

<table>
<thead>
<tr>
<th>Metrics</th>
<th>SWS</th>
<th>CCS</th>
<th>PBS</th>
<th>DIE</th>
<th>Our</th>
</tr>
</thead>
<tbody>
<tr>
<td>PSNR</td>
<td>6.03388</td>
<td>5.22218</td>
<td>6.62852</td>
<td>6.25826</td>
<td>6.84237</td>
</tr>
<tr>
<td>MSSIM</td>
<td>0.37818</td>
<td>0.23310</td>
<td>0.26904</td>
<td>0.21429</td>
<td>0.42201</td>
</tr>
</tbody>
</table>

The average runtime is generally tested to measure the efficiency of the approach in enhancing the low-light images. The runtime and average value of each method for six low-light instrument images are given in Table 2.
Fig. 5. Visual comparison with state-of-the-art low-light image enhancement methods
As can be seen in Table 2, the proposed approach takes less time-consuming compared with SWS, PBS, and DIE. However, the reason why SWS takes less time is that most of its operations are pixel calculations.

Comparing the all experiments, we notice that the proposed approach has better performance on the visual effect, histogram distribution, and objective metrics as well as the time-consuming comparison than other methods. In addition, the high-quality instrument images enhanced by the proposed approach are conducive to be used as input for computer visual tasks.

Table 2. The average runtime comparison of different methods

<table>
<thead>
<tr>
<th>Image</th>
<th>Index</th>
<th>SWS (s)</th>
<th>CCS (s)</th>
<th>PBS (s)</th>
<th>DIE (s)</th>
<th>Our (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Time/s</td>
<td>4.6801</td>
<td>2.5263</td>
<td>5.8515</td>
<td>2.9098</td>
<td>3.0705</td>
</tr>
<tr>
<td>B</td>
<td>Time/s</td>
<td>3.8456</td>
<td>3.0998</td>
<td>6.6253</td>
<td>3.5692</td>
<td>3.0974</td>
</tr>
<tr>
<td>C</td>
<td>Time/s</td>
<td>3.6016</td>
<td>2.2444</td>
<td>5.7011</td>
<td>3.4401</td>
<td>3.2506</td>
</tr>
<tr>
<td>D</td>
<td>Time/s</td>
<td>3.5130</td>
<td>2.8978</td>
<td>5.7673</td>
<td>3.7242</td>
<td>3.1096</td>
</tr>
<tr>
<td>E</td>
<td>Time/s</td>
<td>3.4510</td>
<td>2.1953</td>
<td>6.0553</td>
<td>3.1808</td>
<td>3.1639</td>
</tr>
<tr>
<td>F</td>
<td>Time/s</td>
<td>5.0076</td>
<td>2.3391</td>
<td>5.6817</td>
<td>3.2166</td>
<td>3.0484</td>
</tr>
<tr>
<td>Average value</td>
<td>4.0164</td>
<td>2.5504</td>
<td>5.9470</td>
<td>3.2836</td>
<td>3.1234</td>
<td></td>
</tr>
</tbody>
</table>

CONCLUSION

In this paper, for enhancing the low-light instrument images, we introduce an image enhancement approach based on illumination estimation to effectively handle low contrast, low light, and latent noise. The important idea is how well the illumination image is optimized to obtain a refined image for the low-light instrument image enhancement. Further, we prepare a new low-light instrument dataset for detecting the instrument with YOLOv4, while optimizing the illumination image by designed an optimization function and a Gamma correction to obtain a well-estimated illumination image. Besides, a bilateral filter is utilized to remove the noise. The experimental results demonstrate the effectiveness of our approach in improving visual quality under low-light scenes. What is more, it can meet high visibility input and the real-time requirement in vision-based applications. Besides, our future work is combining image enhancement methods with instrument recognition approach research to improve the accuracy of detection and recognition of robotic inspection substation meters under many conditions such as insufficient lighting.
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REFERENCES


