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Accelerated Dual Network Model for Low-Exposure Image Enhancement

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الملخص:

عندما تعمل طرق تحسين الصورة التقليدية على تحسين الصورة منخفضة التعريض للضوء ، فإنها عادة ما تقوم على تحسين السطوع وتتجاهل مشكلة الضوضاء. إلى جانب ذلك ، تستخدم أساليب التعلم العميق الحالية الشبكة من طرف إلى طرف لتتعلم مباشرة علاقة التعيين بين الصورة منخفضة التعريض والصورة العادية ، متجاهلة المبدأ المادي لتشكيل الصورة منخفضة التعريض . لحل مشكلة الضوضاء، يقدم هذا البحث طريقة تحسين الصورة منخفضة التعريض تعتمد على نموذج الشبكة المزدوجة التدريجي من خلال تحليل الأسباب الأساسية لتدهور الصورة. تتضمن الطريقة المقترحة جزأين الأول وحدة تحسين الصورة والثاني وحدة تقليل التشويش للصورة. يعتمد بناء كل وحدة أيضًا على الفكرة التقدمية من خلال النظر في تغيير سطوع الصورة من الظلام إلى الضوء واستعادة الصورة من الخشنة إلى الدقيقة ، بحيث تكون النتيجة المحسّنة أقرب إلى الصورة الحقيقية. علاوة على ذلك، لتدريب الشبكة بشكل أفضل، تم تصميم وظيفة فقدان القيود ثنائية الاتجاه، مما يجعل نتيجة التعلم لنهج شبكة البيانات الحقيقية من الاتجاهات الإيجابية والسلبية لنموذج تدهور الصورة. تظهر النتائج التجريبية أن الطريقة المقترحة أكثر فعالية من بعض التحسينات الحديثة الأخرى.

Abstract:

Traditional image enhancement methods only consider the increase in brightness when enhancing low-exposure images, ignoring the problem of noise amplification during the process. Current deep learning-based methods, on the other hand, use end-to-end networks to learn the mapping relationship from low-exposure images to normal images without taking into account the physical principles of low-exposure image formation or the problem of noise amplification. In order to address the aforementioned issues, this paper examines the primary causes of image degradation and proposes a low-exposure image enhancement method based on a progressive dual network model. An image enhancement module and an image denoising module are both included in the method. Each module is built in a progressive manner, taking into account the image's brightness change from dark to light. This paper constructs a two-way constrained loss function to make the network learning result approach the real data from the positive and negative directions of the image degradation model to achieve dynamic balance, in order to better train the network. This article compares subjective and objective experiments with some mainstream methods in order to verify the efficacy of the method described in this article. The experimental results show that the results obtained using the method described in this article are more accurate and yield better performance indicators.

Keywords Bidirectional, constrained, loss, function, progressive, low- image enhancement, dual network.

1. Introduction:

Image obtained under low lighting conditions such as at night. Insufficient exposure often results in images with low visibility and poor details. Visible, large noise interference, uneven illumination and other problems. Low illumination the image not only gives the observer a negative visual impression, but seriously affect the computer vision system based on image information normal work. Performances such as resolution and “exposure time have significantly improved as a result of the development of various industrial camera equipment technologies. However, using hardware to increase resolution is costly and has limited generalization ability. It is difficult to achieve universality. Therefore, many researchers began to use image enhancement Strong technology, follow-up processing of the image, improve the quality of the image [1].” Figure 1 is an example of image enhancement, where the first line is a low-exposure image; the second behavior uses the method of this paper to carry out the brightness enhancement image. The image enhancement algorithm brightens the low-exposure image. The degree, details, etc. have been greatly improved. Therefore, the low exposure Optical image enhancement technology is used in target detection, intelligent driving, traffic monitoring, remote sensing images and other fields have very important value.

“In the past few decades, image enhancement technology has developed rapidly; many methods have been proposed to solve the problem of low-exposure image enhancement[2]." “At present, there are mainly three methods for image enhancement, the enhancement methods based on histogram equalization, based on The enhancement method of Non-linear Point Transforms (NLPT) theory [6, 7]”. The emergence of Enhancement method based on deep learning. “The main idea of the enhancement method based on histogram equalization is to the pixel dynamic range of image histogram

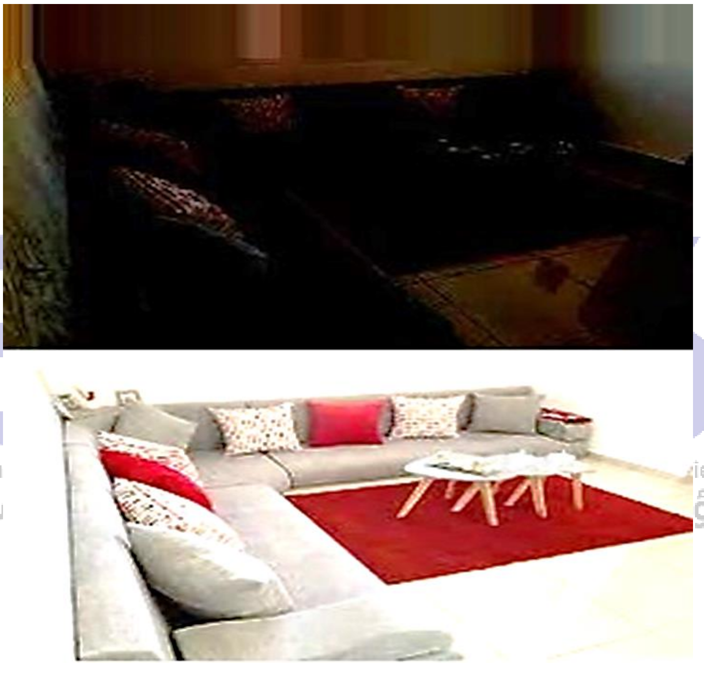


Figure 1 Low-exposure image enhanced by the method Schematic

statistics is stretched, and by increasing the contrast of the image to achieve the purpose of enhancing the visual effect[10, 11].” This kind the enhancement algorithm mainly includes local and global histograms Equalization. This method is dealing with images with too dark foreground and background at the same time, due to the small amount of calculation, this kind of method also has advantages in processing time, but it is often if the area is over-enhanced, there will be problems such as loss of detail and color cast. Regarding the problems of the histogram equalization enhancement method, some improved algorithms Laws have been put forward one after another. Contrast enhancement and denoising of exposed image frames, a new image enhancement method was proposed. The framework uses a local adaptive method based on pixels to advance Line denoising, noise can be eliminated while maintaining texture details, and at the same time "Adaptive enhancement of brightness information based on dark channel

Prior defogging method Strong parameters overcome the problem of over-enhanced or under-enhanced images Mustafa [3]." Proposed a method including "color channel stretching; histogram average the pipeline method of remapping can achieve better results Abirami, eta [4, 5]." use the method of pyramid layer histogram matching to increase Strong image contrast, for maximizing the extraction of image information. Although the enhancement algorithm based on histogram equalization has Great advantage, but because the image is considered in the process of brightness enhancement like the overall statistical characteristics, so when dealing with complex scene images, Cannot achieve good results. The main idea of the theory is providing dynamic range compression of non-linear transforms such as the gamma non-linearity, the logarithm function, as well as the power-law function on the original image. The characteristics (or lighting characteristics) are determined by the joint action.

$$Le = Ne \, . \, l \qquad \text{Formula (1)}$$

In the low-exposure image formation process, Le represents the low-exposure image, ne is the normal exposure image, L is the illuminance image, and the sign stands for element-wise dot multiplication. Image brightness based on NLPT theory the core idea of the enhancement algorithm is to first estimate the illuminance image L, and then remove the L component from the low-exposure image Le to obtain a normal-exposure image like Ne, its mathematical expression is:

$$Ne = Le \, . \, l^{-1} \qquad \text{Formula (2)}$$

"Following Brady proposed NLPT on the human visual system after theory, image enhancement methods based on NLPT theory are widely used Research. Based on the single-scale NLPT theory [6, 8]." A multi-scale NLPT color restoration algorithm is proposed. Line image enhancement while maintaining color consistency. Figure (1) Low-exposure image (the first row) and the image enhanced by the method in this paper ((the first row) Second line) Schematic Combined with NLPT theory, a low-exposure image based on fusion is proposed. The imageenhancement method not only protects the details but also improves the contrast. Inspired by similar visual systems, designed an image-enhanced multi-exposure fusion frame to provide accurate contrast and brightness. Proposed a priori refinement of structure perception Degree graph, and calculated on the red, green, and blue channels to enhance image. Although these methods can achieve better results in some cases Results, but their effects on reflectivity and illumination in the NLPT model. There are still limitations when solving, because the design is suitable for various fields the image decomposition constraint of the scene is the main difficulty in image enhancement. This In addition, since solving the reflectance map is an ill-conditioned problem, a rough estimation can easily lead to overexposure or underexposure in the result of image enhancement Light phenomenon. “With the development of artificial intelligence and neural networks in the field of image processing outstanding performance in the field, based on deep learning methods in the field of image enhancement The domain has been rapidly developed[9,10].” Proposed method based on deep the method of high-degree self-encoding enhances and denoises low-exposure images. “The brightness of the image is improved, and the overexposure of the image is avoided. Ahmed , eta [11, 13].” “Created a Low-exposure image data set, and designed a fully convolutional end-to-end network to achieve image enhancement. Brady, eta [14, 22]”. “Human vision theory and convolutional neural network are combined to decompose low-exposure images into reverse Emissivity map and illumination map, and use the enhancement network to achieve image brightness Enhanced. Goodall, eta [23, 24, 25]”. “First proposed the use of unpaired low/normal Brightness of the image to train the image brightness enhancement network, this training strategy slightly eliminates the dependence on paired training data. Menteş [28, 29].” Excluding Learn the direct mapping between low-brightness and normal-brightness images. Instead, it estimates the mapping between the image and the light map to enhance the exposure insufficient images, this method enhances the network learning to complex images Adjustment ability. Although the above methods can achieve better results, because these deep learning-based methods are end-to-end direct learning. Learning the mapping relationship between low-exposure images and normal images while ignoring low-exposure images while explicitly mentioning denoising, the physical principles of light image formation since this process may rely solely on traditional denoising methods, the image may suffer as a result. There are issues after strong, such as detail loss and noise amplification. Based on the above analysis, this article focuses on the existing low-exposure image enhancement Due to the method's limitations, a method based on NLPT theory is proposed Progressive dual-network low-exposure image enhancement model (Figure 2). Should the network takes low-exposure images as input and uses convolutions of different scales; the core performs feature extraction, and finally learns the images in the NLPT model. The illuminance diagram and then substitute the illuminance diagram into the NLPT model to calculate image with increased brightness. Then for the enhancement process the problem of noise amplification is to pass the enhanced image through another image Noisy network to get the final enhancement result. Such as Down:

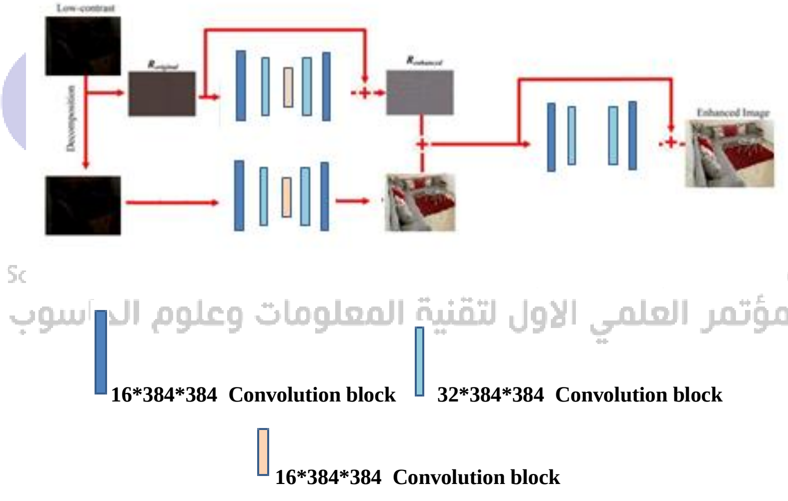


Figure2 Progressive dual-network low-exposure image enhancement model

1. Propose a progressive dual-network low-exposure image enhancement Model. The whole model is aimed at low brightness and low exposure image enhancement. The progressive idea Module and image denoising module are used to solve the problem of noise amplification and image enhancement.
2. In the two modules of the image enhancement model, adopt Use progressive thinking to construct its network framework, to realize the rough detailed repair process, in order to obtain better enhancement results.
3. Considering the reversibility of the image degradation theory, a two-way

constrained loss function is used for network learning, from image degradation model.

The loss calculation is carried out in the positive and negative directions of the type, so that the learned information more complete. The following is the paper's structure: The suggested approach is the emphasis of Chapter 2, while the experimental method and comparative experiment are detailed in Chapter 3. Explain in detail, Chapter 4 outlines the whole content of the paper as well as future research prospects

2. Progressive image enhancement method

2.1. Network framework

For existing methods, there is loss of detail after image enhancement and the problem of noise amplification, this paper proposes a progressive dual network Low-exposure image enhancement model, which includes image brightness enhancement model. The two sub-networks of block and image denoising module, the overall framework constructed is as shown in Figure 2. Researcher combine network design with physical model of image enhancement combining, first adopt the progressive idea to realize the low-exposure image. The brightness is enhanced, and then the noise that appears in the enhanced image is added, which is a difficult task. Finally, the image denoising process is applied to the brightness enhancement result. It's important mentioning that, in order to achieve better image enhancement results; this article uses progressive thinking to achieve brightness enhancement and noise reduction from course to fine levels in two modules of image enhancement and image de-noising. The difference between the image de-noising module and the enhancement module is that image noise usually considered as an additive noise, in the image de-noising module, this is the case. Finally, a subtraction operation is used to obtain the final output result, which is obtained by directly subtracting the input image from learned noise. Network for better training. This paper builds a loss function with positive and negative bidirectional constraints to train the network based on the reversibility of image degradation theory. In section 2.2, the specific internal Content will be discussed in further detail depth.

2.1.1. Image Brightness Enhancement Module

Considering that the brightness increase in real scenes is changing from dark to bright Process, this article proposes a progressive image enhancement module, Low-exposure images achieve the brightness of the image from course to refined twice successively and color enhancement to complete the process of image brightness enhancement. The implementation process of the network module is described as follows. The input of the image improvement module (the upper dashed box) in Figure 2 is a low exposure image, and the module's two sub-frames the illuminance diagram is the output, and the input and output are the red, green, and blue aisles. This module includes two steps: preliminary brightness reconstruction and brightness enhancement. The framework of the first step contains five conventional layers, and the first two layers of the network use the convolution operation realizes the down-sampling of the feature map, which can guarantee the effect of down sampling also avoids the loss of information caused by down sampling lose. By down sampling to reduce the size of the feature map, the convolution can be expanded the nuclear receptive field, so that you can only be learnt the volume of 3*3 range of information. The product core can be learnt a letter in the range of 7*7 after two size reductions. In addition, order to ensure that the final illuminance map and the input image is the same size, using 2 de convolution operations in the network to achieve the purpose of increasing the size, but also to facilitate the calculation of gradient descent. The brightness enhancement network framework of the second step is similar to the first step. The purpose of this step is to refine the enhanced image. This part of the network only four convolutional layers are set in, and by using fewer network training parameters to improve network performance. This article also gives experiments in section 3.2; it is proved that using four convolutional layers is better than using five convolutional layers directly to give improved result. This module is to ensure the effectiveness of the network and to produce greater use of the original image information, first compare the preliminary enhancement results with the original. The image uses a splicing operation, and then uses two convolutions and deconvolutions Product operation to achieve further enhancement of the image. In these convolutional layers, each layer contains two types of parameters, weight and deviation, which are calculated as follows mode:

$$G(x) = y * x + k \qquad \text{Formula (3)}$$

In the formula, G is the feature map obtained after convolution, and y, k are respectively for weights and deviations, x is the input, represents the convolution calculation. In the entire framework, there is a layer of excitation behind each convolutional layer. The function is defined as follows:

$$Ne(x) = Max(0, G(x) \quad \text{Formula (4)}$$

Where G(x) is the result of convolution, Ne(x) is the result of the function. The purpose of the activation function is to be effective save information while removing invalid information, thus speeding up training.

2.1.2. Image Denoising Module

It will be affected by a variety of noises in addition to insufficient light in the imaging process of low-exposure images. The contrast is relatively low in the case of low brightness due to the image, and the noise is difficult to detect. However, the image is enhanced by the low exposure, the noise is also enhanced. As shown in the image denoising module in Figure 2, a noise removal module is provided. The network design idea of this module is similar to that of the enhanced module, adopting progressive has twice to learn the noise image from course to fine, realize removal of noise from the reconstructed image of brightness. Pass to many within the module convolution of feature maps of various sizes to broaden the receptive field and learn more various features. The purpose of network module is to learn the noise of the image, and it is usually considered as an additive noise, so a subtraction operation is used at the back end of the two sub-blocks, which will increase solid image is subtracted from the noise component learned by the network to get the image after noise. Since the network module does not need to learn noise components, it is necessary to consider the image feature issue. Information reuse, similarly, in the denoising network the module should not use the splicing operation found in the enhanced module.

2.2. Loss function

The execution function of the network model mainly depends on the loss function definition. In the network model learning of image restoration, the average Mean Squared Error or Mean Absolute Error. Error indicators such as Mean Absolute Error to define the loss function. However, due to the low brightness of low-exposure images, using only error indicators such as Mean Squared Error or Mean Absolute Error may lead to results Structural distortions. So in order to improve the vision quality, this paper designed as consists of structural loss and two-way constraint loss to construct a new. The loss function is used to train the network. Among them, the image brightness enhancement module the loss function is defined as follows:

$$lo_E = lo_S + lo_F \quad \text{Formula (5)}$$

Lo is the structural similarity loss function (os), (of) is the two-way constraint in the formula. The image denoising module's loss function is defined as:

$$l_{ON} = l_{OSP} + l_{OSN} \qquad \text{Formula (6)}$$

Where (L_{osp}) is the forward structure loss function, (L_{osn}) is the reverse structure loss function. The two-way constrained loss function is derived from the pros and cons of the image degradation model. The directions are defined by approximating to the real data respectively. Structure similarity loss function is used to ensure the integrity of the image structure information of specific definition will be given below.

2.2.1. Structural similarity loss function

While obtaining global information, the network also Inch feature map convolution to learn structural details, so Multiscale Structural has used Similarity, quality evaluation method as a loss function to maintain Image structure to avoid blur. The way to obtain it is:

$$MultiS(v1, v2) = lo(v1.v2) \quad \prod_{k=1}^{n} \quad d(v1, v2)_1^{c1} \quad Si(v1.v2)_1^{n} \qquad \text{Formula (7)}$$

Among them, v1, v2 are the corresponding image input, lo(v1,v2) is the brightness Information, d is contrast information, lo is structural similarity, k is pixel Coordinates, n is the total number of pixels, are the importance of adjustment Parameter, the greater value of Multiset, more complete the structural information, The similarity loss function is defined as:

$$l_{Multis}(v1, v2) = 1 - MultiS(a1.a2) \qquad \text{Formula (8)}$$

Therefore, based on the above formula (8), the image brightness enhancement mode the structural similarity loss function Los of the block can be defined as:

$$l_{os} = l_{Multis}\big(w1, g(le)\big) \qquad \text{Formula (9)}$$

Where w1 represents the real normal exposure image, le is the low exposure image; g (le) is the network output result.

2.2.2. Two-way constraint loss function

The purpose of enhancement module learning is to get an accurate illuminance map Lo = g (Le), and then calculate the enhanced Image Ne= le.g(le)$^{-1}$. The loss function is defined by traditional deep learning. The method is primarily accomplished by connecting the network output and the actual data. The difference is minimized in order to train the network and ensure that the output result is correct. The real data was approaching quickly. As a result, the image will be used in this article as well. To train the enhanced network module, the absolute value of the difference between the enhancement result and the normal exposure image is minimized using the following calculation method:

$$lo_P = \sum_{i=1}^{n} \mid wi - \big(Le * -g(le)\big) \mid \qquad \text{Formula (10)}$$

According to formula (1), the researcher used reverse deduction to verify the accuracy of the illuminance map g(le) output by the enhanced network, which is approximately g(le) is substituted into the formula (1), using a real image to correspond with - g (le) is Multiply the resulting degraded image by the network's low-exposure image. In comparison, the network model output results are more accurate if the network is closer to the input image le. Based on this concept, this article will reverse the process is being introduced into network training and the above formula (10) have been defined? Is the forward propulsion loss, and the reverse propulsion process is defined as the reverse propulsion loss, so that the network can approach the real result in both directions.

Near input, achieve dynamic balance and improve network accuracy. Based on the above analysis, this paper proposes a two-way constrained loss function, which it is defined as follows:

$$lo_F = lo_P + lo_n \qquad \text{Formula (11)}$$

$$lo_N = \sum_{i=1}^{n} \mid le_i - \big(w * g(le)\big) \mid \qquad \text{Formula (12)}$$

Indicates a loss of reverse propulsion. The concept of two-way constraint loss is useful not only in the image enhancement module, but it can also be used in the denoising module. The same foundation Based on the concept of a two-way constraint, this article defines the forward and reverse structure loss Functions for training the image denoising module, which are respectively expressed as:

$$lo_{SP} = l_{MultiS}(w, w_n - g(w_n)) \qquad \text{Formula (13)}$$

$$lo_{Sn} = l_{MultiS}(\, w_n \,, w + g(w_n)) \qquad \text{Formula (14)}$$

Among them, w_n is the noisy data set, $g(w_n)$ is the denoising network learning resulting noise.

2.3. Network training

2.3.1. Training method

Since this enhancement and denoising modules are trained separately, when the loss function is minimized, the loss functions of the two modules are also different. The image enhancement module was trained using formula (5), and the image denoising module was trained using formula (6). The RMSProp gradient descent method is used for optimization. The training process of the entire network is shown in Algorithm 1.

Algorithm 1. Network training process.

Input: the number of single training samples n
Output: Illuminance map g(le), image after denoising
step:
for d = 1; d ≤ repetitions do
  Low exposure image set le;
  Output enhanced image: Ne←g(le);
  The gradient descent method updates the image enhancement loss function;
end
for d = 1; d ≤ repetitions do
  Add noise image Wd; RMSProp algorithm
  Output denoising image: Ne ←g(wd);
  The gradient descent method updates the image denoising loss function;
end
End.

Table 1 Network parameter table

Network part	Convolutional layer	Output dimensions	Convolution kernel number	Convolution kernel Size	Stride length
Image brightness enhancing module	Input	3*384*384	*	*	*
	1	16*384*384	16	3*3	1
	2	32*192*192	32	3*3	2
	3	64*96*96	64	3*3	2

	Output	**3*384*384**	**3**	**3*3**	**1**
Image denoising module	**Input**	**3*384*384**	*****	*****	*****
	1	**16*384*384**	**16**	**3*3**	**1**
	2	**32*192*192**	**32**	**3*3**	**2**
	3	**32*192*192**	**32**	**1*1**	**1**
	`Output	**3*384*384**	**3**	**3*3**	**1**

2.3.2. Network Settings

The entire network has 14 convolutional layers, including enhancement and denoising. Each module has three convolutional and two de- convolutional layers. In addition to the 3*3 size convolution kernel, 1*1 size convolution kernel is used in all convolutional layers to improve model nonlinearity, reduce the number of parameters, and increase calculation speed. Table shown in the specific parameter setting.

3. Experimental results and analysis

The effectiveness of the method proposed in this article will be tested on the synthetic image dataset and the real-world image dataset, and it will be compared to three other image enhancement methods. GHP [15], LSSC [16], and SVD [17] are the three methods. Furthermore, the results of the low-exposure image after only the first brightness enhancement module, as well as the denoising results of the image after the brightness enhancement, are shown separately to verify that only the image enhancement causes the problem of noise amplification, and to further explain the effectiveness of the progressive dual network model proposed in this paper. Related experiments are described in section 3.3.

3.1. Experimental design

“There are two databases used for image enhancement module training[20].” One is the low-exposure image pair database. which contains 20 low-exposure images and corresponding normal-exposure images. The size of each image is 480*640. Most of the images in low-exposure image pair database are obtained by adjusting the exposure time in natural scenes. The method in this article will use 10 image pairs of the database for training, and the remaining 2 image pairs for testing. The other database is a synthetic database.

Part of the low exposure data set and the corresponding normal exposure data set

Part of the noisy data set, as well as the noise-free and clear data set

Figure 3 Database instance

3.2. Objective indicators

In order to prove the performance advantage of the method in this paper, Naturalness Image Quality Evaluator. (NIQE) [18] Was used, Blind/Reference less Image Spatial Quality Evaluator (BRISQUE) [19] and color Difference (ΔEITP) [21] three indicators to carry out various methods objective comment. NIQE is a full-parameter image quality evaluation index, calculation method of the difference between each pixel is:

$$\mathrm{l_{Sn}} = 10\ \log(\frac{\mathrm{J}^2}{\mathrm{MeanSR}}) \qquad \text{Formula (15)}$$

Among them, l_{Sn} refers to the maximum value of pixels in the image, generally taken 255, MeanSR refers to mean square error, MeanSR is calculated as follows:

$$MeanSR = \frac{1}{m\,n}\sum_{i=1}^{m}\sum_{i=1}^{n}\ (x(i,j) - y(i,j))^{\ 2} \quad \text{Formula (16)}$$

Where m and n are the image's length and width, and x and y are the image's x and y coordinates. Higher value of NIQE, will give image quality. BRISQUE is a full-parameter image quality evaluation index with value points between 0 and 1. The larger value, the smaller difference, and the image quality will be better amount. Estimate method is as follows:

$$BR = l\,o(x1, x2)\,.\ C(x1, x2)\,.\ S(x1, x2) \qquad \text{Formula (17)}$$

Where l, c, and s represent the brightness, contrast, and similarity of the three structural aspects. ΔEITP can test the enhanced image and real data. The difference in chromatic aberration Convert the RGB image to Lab color space first. In the meantime, use the ΔEITP method to calculate the color difference between two images. Similar to the color difference E between each pixel corresponding to y and L, as the color difference between two images is calculated using the following formula:

$$MeanSR = \frac{1}{Ne}\sum_{i=1}^{Ne} f(w_i\,,\ l_i\,) \qquad \text{Formula (18)}$$

Where Ne is the number of pixels, and **f** represents two images in Lab space and the color difference of each pixel between the images, w is the network output image, L is for real data, the lower color difference value, and the closer color is to the real image.

3.3. Experimental results

The final result of image enhancement on some images in the data set, as well as the synthetic database result, can be seen in this section. The subjective effect is the most direct feeling of the human eye, as shown in Figure 4. As shown, the method in this article and the other three methods are obtained in different scenarios. The result can be seen in figure 4.

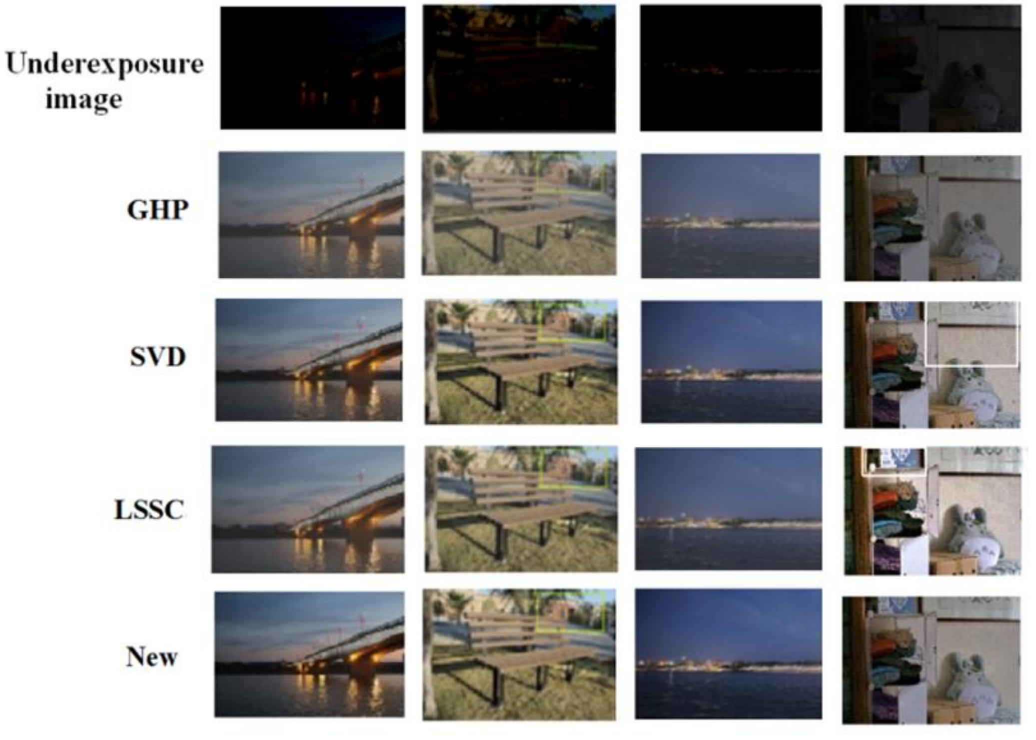


Figure 4 Image enhancement results

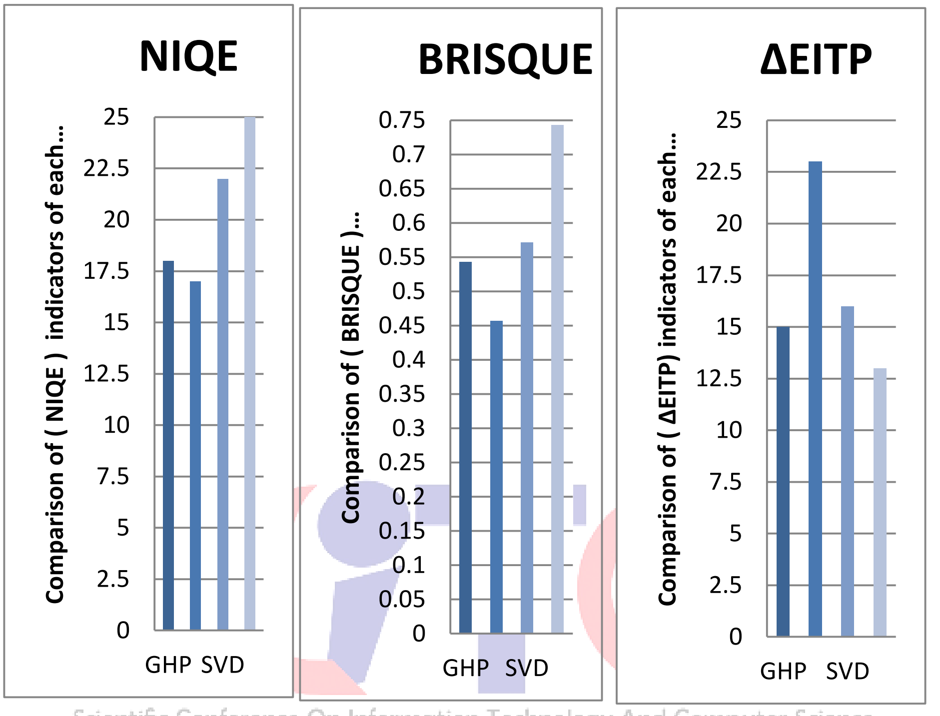
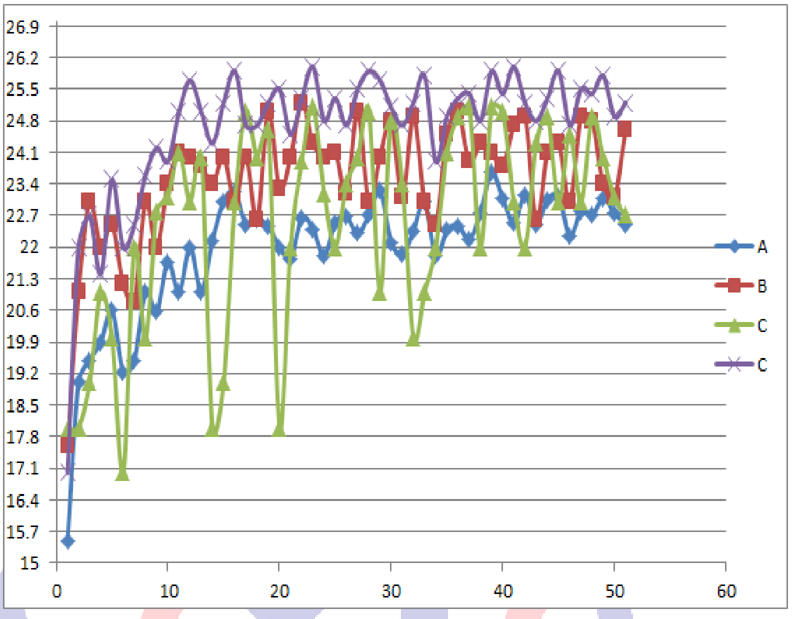
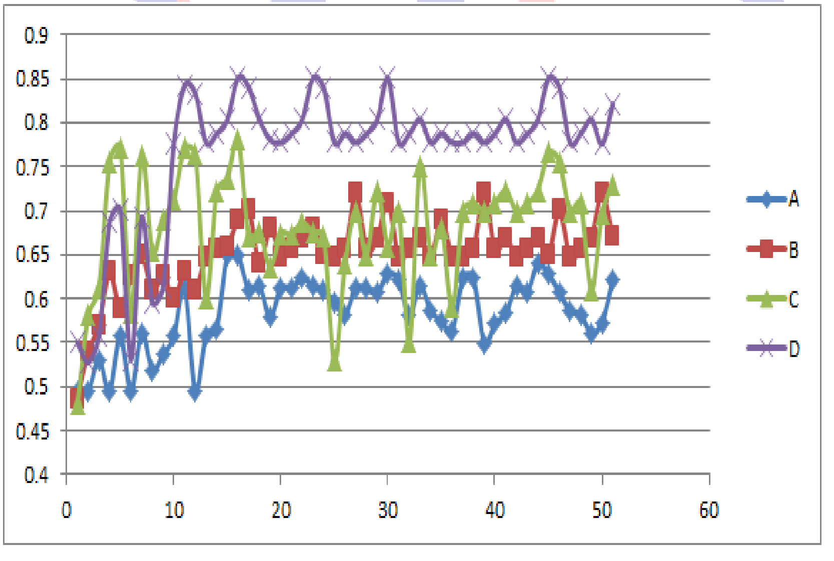


Figure 5: Comparison of NIQE, BRISQUE and ΔEITP.

The LSSC and GHP methods have produced overexposure while obtaining rich detailed information and the problem of noise amplification has also occurred. For example, the area in the white frame can be observed when the overexposure is obvious, the brightness of all images is higher than the real image, and the serious color cast problem can be seen in the third column. SVD achieves more natural results, but it is also accompanied by slight noise and color cast effects; Compared with these methods, new method has achieved brightness is enhanced, the color of the image is more natural, and there is no extra Noise, the result is also the closest to the real image.



(a) NIQE indicator result graph



(b) BRISQUE indicator result graph

Figure 6: The NIQE, BRISQUE graph results

4. Discussion

This article uses the overview in 3.2. The objective indicators to compare the methods. Figure 5 shows this method and the other three methods are used to enhance 20 images to obtain the objective indicators NIQE, the average value of BRISQUE and ΔEITP, last column data is the result of the method in this article. It can be seen by comparison the NIQE, BRISQUE and Compared with the other three methods, the ΔEITP value is the best. Finally, verifying the progressive dual network proposed by this method network model and the effectiveness of the two-way constrained loss function, the constructed network has done a lot of experiments for comparison. Figure 6 shows the objective of the results obtained by several deformed networks of the double progressive network framework, the change trend of indicators NIQE and BRISQUE. Among them, the ordinate is the objective index value; the abscissa is the number of iterations of network training. In the graph purple line shows the result of the progressive dual network model in this article. The green bar shows that the two-way constraint loss is not used. The red line is added on the basis of the method in this paper Deep network depth (5 convolutional layer structure used in the fine part). The blue line is the enhancement module with only the first part the result value obtained. From figure (a) and (b), the trend of the indicator curve can be seen that only the results obtained by the first part of the enhancement module are calculated NIQE and BRISQUE values are relatively low; the other three network structure packages the enhancement result obtained by the progressive enhancement network with the denoising module Both NIQE and BRISQUE values have been significantly improved; but from the curve point in terms of the trend of drawing lines, increase the depth of the refined part of the network. Compared with using of four convolutional layers, the objective index value is reduced; from red line the trend of the bar and the purple line can be seen, using the training of the two-way constraint loss function on the network further improves accuracy of the network has a higher index. Thus, it is clear that network structure proposed in this paper is effective and robust.

5. Conclusion:

This paper proposes a low-exposure image enhancement method with progressive dual network architecture. The aim of solving the problem of brightness degradation and noise degradation in low-exposure images, the progressive idea is used to first improve the brightness and color of the image, and then remove the image. For these two-step processes, this paper creates two gradient modules to match the brightness change of the real scene from dark to bright, and the image recovery process from course to fine, so that the results are more natural. In order to better train the network, this paper proposes a loss function with bidirectional constraints, which can not only approximate the real result forward, but also approximate the input in the reverse direction, achieve dynamic balancing and improve the network accuracy. In order to verify the effectiveness of the proposed method, a large number of experiments were carried out in this research, and compared to multiple methods from the subjective and objective sides; the experimental results also proved that the method in this research has a better performance. In the future, we plan to combine video surveillance applications with image optimization algorithm research to improve the monitoring capabilities of real-time video surveillance at night or under insufficient lighting conditions.

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