Adaptive Image Enhancement Algorithm for Image Quality Improvement

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Abstract. Images are often affected by factors such as lighting, environment, and equipment during daily collection, resulting in a decrease in quality, low contrast, insufficient brightness, and blurry details. To improve the visual quality of images, this paper proposes an adaptive image enhancement algorithm based on image quality. This method first performs grayscale conversion and preprocessing on the input image, and get image parameters from three dimensions: contrast, brightness, and clarity. Dynamically adjust the enhancement parameters of the algorithm based on the read image parameters, including contrast limited adaptive histogram equalization, gamma correction, Retinex simulation enhancement, and sharpening processing. This system can be applied to both color and grayscale images, and the enhancement strategy has high adaptability. The experimental part comprehensively evaluates the enhancement effect using indicators such as structural similarity, peak signal-to-noise ratio, natural image quality assessment, blind reference image quality assessment, image entropy, and color richness. The research results indicate that the method provided in this paper can enrich the image details. However, there are still issues such as limited color enhancement and significant structural changes during the enhancement process. Further research will focus on optimizing enhancement strategies and introducing deep learning methods.

Keywords: Image enhancement; Image quality assessment; Adaptive processing; Visual rating.

1. Introduction

In the field of image processing, improving image quality has always been one of the important research directions. Due to limitations such as shooting environment, equipment performance, or lighting conditions, actual captured images often have issues such as low contrast, insufficient brightness, and blurry details. This not only affects the visual perception of the human eye but also interferes with subsequent image analysis, recognition, and understanding tasks. Therefore, designing a system that can automatically recognize image quality and improve image quality is of great significance [1].

Traditional image enhancement methods often use fixed parameters or a single strategy, such as histogram equalization, gamma correction, or sharpening filtering [2-4]. Although it is useful in specific places, they lack adaptive judgment of image quality, which can easily lead to poor enhancement effects and single processing objects. In recent years, some studies have tried to introduce image quality assessment indicators to guide the enhancement process, but there are still problems, such as limited evaluation aspects, single enhancement strategies, and inflexible problem handling.

Therefore, this paper proposes an adaptive image enhancement method based on image quality assessment. This method first performs grayscale conversion and preprocessing on the input image, and quantitatively evaluates the image quality from three dimensions: contrast, brightness, and clarity [5-9]. Calculate the visual score based on the evaluation results and dynamically adjust the enhancement parameters accordingly, including contrast-limited adaptive histogram equalization, gamma correction, Retinex simulation enhancement, and sharpening processing. This system can be applied to both color and grayscale images, and the enhancement strategy has high adaptability.

The experimental part comprehensively evaluates the enhancement effect using indicators such as structural similarity, peak signal-to-noise ratio, natural image quality assessment, blind reference image quality assessment, image entropy, and color richness [10-15]. The results show that the

proposed method has good performance in improving the overall visual quality of images, especially in terms of brightness and clarity. However, there are still problems with the enhancement strategy relying on empirical rules, Retinex simulation simplification, and limited color enhancement in this method. Further research will focus on adding the intelligence of enhancement algorithms and the introduction of deep learning methods.

2. Method

This paper proposes an adaptive image enhancement method based on image quality assessment, aimed at solving common problems such as insufficient brightness, low contrast, and blurry details in actual images. This method allowed users to quantitatively analyze the image quality, build a visual evaluation mechanism based on which to dynamically adjust the gain parameters, and provide accurate gain.

The entire system includes image preprocessing, quality evaluation, viewpoint calculation, selection of enhancement strategies, and image output modules. In an image preprocessing stage, the system first reduces the input image evenly to a fixed size, converts it to a gray image, and then evaluates the quality. Image quality evaluation components quantitatively analyze images in three dimensions: contrast, brightness, and clarity.

Among these, the contrast is calculated by the standard deviation of the gray image, the brightness is measured by the average value of the gray diagram, the edge processing by the Laplace filter increases the clarity, and the difference is calculated to reflect the detail of the image and the abundance of information about the edge. To achieve adaptive adjustment of enhanced parameters, the system introduces a visual scoring mechanism. The score is calculated by weighting the three normalized indicators above, with a range of 0 to 1. The lower the value, the worse the image quality, and the system will automatically increase the enhancement intensity. Visual scoring is not only used to control the numerical values of enhancement parameters, but also to determine whether specific enhancement modules are enabled.

In terms of enhancement strategy, the system adopts different processing flows based on whether the image is a color image. For color images, the system processes the R, G, and B channels separately. If the image contrast is insufficient, contrast limited adaptive histogram equalization (CLAHE) should be applied to enhance local contrast; If the brightness is abnormal, different gamma values should be selected for correction based on the brightness value; Subsequently, the system simulates a multi-scale Retinex model to enhance image brightness and detail, and fuses the original image with the enhanced image; If the clarity is insufficient, sharpen each channel to enhance edge information. For grayscale images, the system sequentially performs the aforementioned enhancement operations on a single channel.

All enhancement parameters, such as CLAHE's cutting limit, Retinex fusion weight, sharpening intensity, etc., are dynamically controlled by visual scoring to ensure that the enhancement process is targeted and adaptive. This method achieves differentiated enhancement of images of different qualities while maintaining a concise processing flow and has strong practicality and flexibility.

3. Experiment and Result

To verify the effectiveness of the proposed image enhancement method, this paper enhanced a poor-quality color image and quantitatively evaluated and subjectively compared the image quality before and after enhancement. The experiment was conducted on the MATLAB platform, with a uniform image size of 256 × 256, and multiple image quality evaluation indicators were used for analysis.

3.1. Original Image Quality Assessment

Before enhancement processing, the contrast of the image was 44.84, the brightness was 63.96, and the clarity was 580.95, all of which were lower than the ideal quality range set (contrast 40-80, brightness 100-180, clarity≥1000). This indicates that the original image is overall dark, with blurry details, insufficient contrast, and poor visual quality. The system processes are based on the evaluation results and expected goals.

3.2. Changes in Image Quality After Enhancement

After adaptive enhancement processing, the quality indicators of the image have significantly improved. The contrast has increased to 49.68, the brightness has increased to 143.37, and the clarity has increased to 1141.5, indicating that the enhancement strategy has a significant effect on brightness correction and detail restoration. Table 1 shows the comparison of quality indicators of the images before and after enhancement. From this, it is obvious that the brightness and clarity have been significantly improved, both approaching or exceeding double, indicating that the algorithm is very effective in improving overall lighting and highlighting detailed textures. In addition, there is a stable increase in contrast, which helps to enhance the sense of hierarchy in the image.

Table 1. Comparison of basic quality indicators before and after image enhancement

	Contrast	Brightness	Sharpness
Original	44.84	63.962	580.95
Enhance	49.684	143.37	1141.5

3.3. Analysis of Image Quality Evaluation Indicator

To further verify the enhancement effect, multiple reference and no-reference image quality evaluation indicators were used in this paper for evaluation, and the results are shown in Table 2

From the perspective of data analysis, the algorithm performs well without reference metrics, such as low NIQE and BRISQUE values, indicating that the enhanced image itself has good naturalness and visual quality, with less distortion introduced manually. In addition, the information entropy is 7.46, indicating that the amount of detail and texture information contained in the image is at a moderate level.

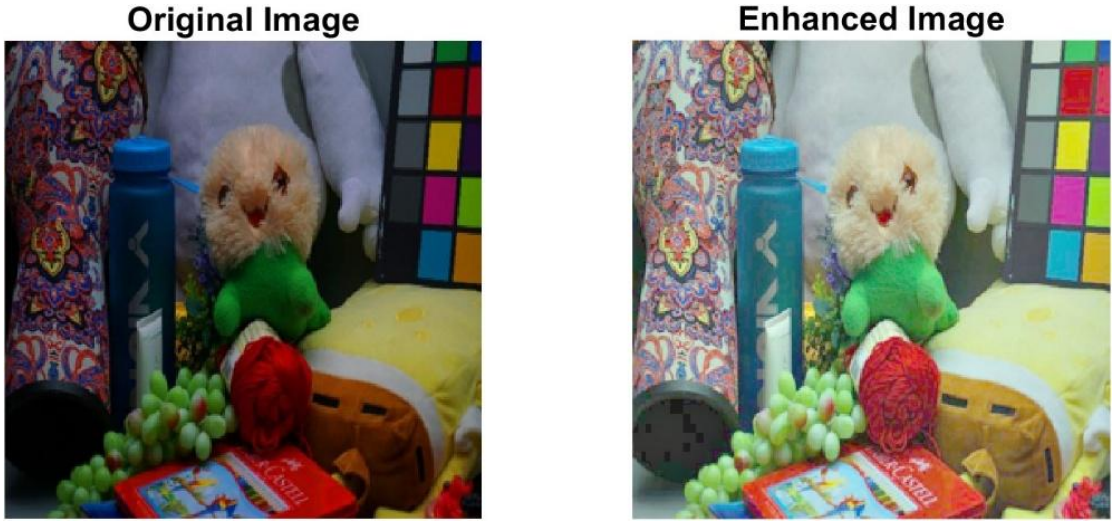
However, there is still room for improvement in terms of performance with reference indicators, such as the significant difference between SSIM and the ideal value of 1, indicating significant differences in structure, brightness, and contrast between the enhanced image and the original image. The PSNR is far below the acceptable threshold of 20dB, indicating that significant noise or pixel-level errors may have been introduced during the processing. In addition, low color richness indicates that the image may appear darker or less saturated in color.

Table 2. Advanced quality evaluation indicators for enhancing images

SSIM	PSNR	NIQE	BRISQUE	Entropy	Colorfulness
0.5975	9.98dB	3.41	6.58	7.46	0.29

3.4. Comparison of the Visual Effects of Images

The effect before and after image enhancement is shown in Figure 1. The original image is generally dark with blurry details, while the enhanced image shows a significant increase in brightness, enhanced edge clarity, and a more natural visual experience. Although the improvement in color saturation is limited, there is a significant improvement in brightness and clarity, which helps to enhance the visual experience of the image.



(a) (b)

Fig. 1 Comparison between the original image and enhanced image. (a) Original Image [16]. (b) Enhanced Image.

4. Method Evaluation and Future Prospects

The image enhancement method proposed in this paper has achieved significant improvements in image quality across multiple dimensions, particularly in terms of brightness and clarity. By introducing an image quality assessment mechanism, the system can dynamically adjust the enhancement strategy based on the actual condition of the image, achieving strong adaptability while maintaining a concise processing flow. The experimental results show that the enhanced image is superior to the original image in terms of brightness, detail, and information content, and also performs well in terms of naturalness and subjective quality ratings.

However, this method still has certain limitations. Firstly, the design of enhancement strategies relies on manually set empirical rules, and the construction of visual scores adopts a linear weighting method, which fails to fully consider the nonlinear relationships or semantic information between various indicators. Secondly, the Retinex enhancement part adopts a simplified multi-scale simulation method that does not include a color restoration mechanism, which may result in color shift or insufficient saturation. In addition, when processing images with very low light or high noise levels, the effect of system amplification continues to change, indicating the need for even greater robustness in complex scenes.

In response to the above issues, next step will attempt to optimize in the following areas in the future. The first step is to introduce deep learning models, such as image enhancement methods based on convolutional neural networks or generative adversarial networks, to achieve more intelligent parameter adjustment and content understanding. Then, optimizing the image quality assessment mechanism, combining subjective scoring with semantic information to construct a more adaptive visual scoring system. Based on that, the next step is to enhance color processing capabilities by introducing color restoration modules or color perception models to improve the visual realism and aesthetics of enhanced images. Finally, the scope of application of the system should be expanded so that it can maintain stable enhancement effects in complex environments.

In summary, the method proposed in this paper has good performance in improving the visual quality of images, providing useful exploration for the intelligence and practicality of image enhancement systems. Future work will focus on in-depth research on enhancing the intelligence of strategies, optimizing evaluation mechanisms, and improving system robustness.

5. Conclusion

This paper proposes an adaptive image enhancement method based on image quality assessment, which solves common problems such as insufficient brightness, low contrast, and blurry details in actual images. By quantitatively evaluating the contrast, brightness, and clarity of the images, a visual scoring mechanism is constructed, and the enhancement strategy is dynamically adjusted accordingly. This method integrates traditional image processing techniques such as CLAHE, gamma correction, Retinex analog enhancement, and sharpening filtering, achieving unified processing of color and grayscale images.

The experimental results show that this method has significant improvement effects in brightness and clarity, and the structural similarity, information entropy, naturalness, and other indicators of the image have been improved, verifying the effectiveness and practicality of the method. However, this method still has certain limitations, such as relying on empirical rules for enhancement strategies, simplifying Retinex models, and limited color enhancement. In the future, the next step is introducing deep learning models to achieve more intelligent enhancement strategies, while optimizing the image quality assessment mechanism to make the system more adaptable and robust in complex scenes.

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