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Research Progress on Image Enhancement Technology Based on Deep Learning

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Abstract:

Image enhancement techniques can improve image quality, making it more suitable for human visual perception or machine analysis needs. In recent years, with the advancement of deep learning, image enhancement methods have seen significant improvements in both effectiveness and applicability. This paper reviews the major advancements in deep learning-based image enhancement techniques, covering typical tasks such as low-light enhancement, super-resolution, and underwater image restoration. It analyzes the mechanisms and performance of different models, and examines their capabilities in noise suppression, detail recovery, and color authenticity. However, current deep learning-based image enhancement methods still face limitations in computational efficiency and practical applicability. To improve deployability, this paper proposes a strategy combining lightweight networks with fully-supervised or semi-supervised learning, achieving effective image enhancement without significantly compromising visual authenticity. Through fully-supervised or semi-supervised approaches, the model maintains stability in scenarios with limited data or significant domain shifts. Future work will focus on inference speed, computational cost, model size, and practical performance on resource-constrained devices as core evaluation metrics, aiming to enhance real-time capability while preserving visual realism.

Keywords: Image enhancement techniques; deep learning; computational efficiency.

1. Introduction

With the widespread use of digital imaging devices, the varying quality of images directly affects subsequent analysis and machine learning tasks. Traditional image enhancement requires manual parameter tuning and has limited adaptability to different scenarios. In recent years, deep learning, through end-to-end learning, can automatically extract features and transformation relationships from limited data, significantly improving performance in areas such as low-light enhancement, noise reduction, contrast adjustment, and color reproduction. Deep learning-based enhancement not only improves visual perception for the human eye but also provides clearer inputs for tasks such as object detection and medical diagnosis. Therefore, systematically reviewing deep learning-based image enhancement methods, analyzing their mechanisms and limitations, is of great significance for selecting and improving methods in practical applications [1,2].

In recent years, deep learning technologies have achieved remarkable breakthroughs, demonstrating high accuracy and adaptability in the field of image enhancement. Deep learning-based image enhancement techniques offer the following advantages: first, they effectively reduce labor costs and adapt to various complex scenarios; second, with their powerful learning and generalization capabilities, they enable more precise image enhancement compared to traditional methods, avoiding cumbersome classification processes and thereby improving image recognition efficiency [3,4]. Representative approaches, such as fully-supervised and semi-supervised methods based on Retinex theory, have significantly improved image brightness and contrast under extremely low-light conditions. In underwater environments, deep learning technologies have also enhanced the stability of image processing in marine scenarios [5]. For example, the team led by Lu-Jian Ye combined deep learning with Retinex theory to design both fully-supervised and semi-supervised low-light image enhancement algorithms. These algorithms excel in brightness optimization and denoising, achieving higher PSNR and SSIM metrics on the LOL dataset and outperforming contemporary methods [6].

In terms of current research trends, mainstream directions encompass typical tasks such as low-light image enhancement, super-resolution, and underwater image restoration. Fully-supervised and semi-supervised methods based on Retinex theory enhance brightness and contrast by decomposing illumination and reflection components; denoising and reconstruction modules based on convolutional neural networks suppress noise while preserving details, improving structural fidelity; the integration of 3D LUTs with deep learning has achieved results in balancing color authenticity and style preservation. However, current methods still face challenges such as high computational costs, limited robustness in real-world scenarios, and strong dependence on datasets. Different application scenarios also exhibit divergent requirements in balancing authenticity, natural appearance, and detail restoration, prompting researchers to explore integrated solutions involving lightweight models, cross-domain transfer capabilities, and multi-task collaboration.

This paper provides a systematic review of deep learning-based image enhancement techniques, focusing on analyzing their core mechanisms, representative models, and performance in typical tasks, aiming to offer actionable insights and references for related research. The structure of the paper is as follows: first, it organizes existing methods and technical approaches; second, it discusses the working mechanisms, experimental results, and main limitations of models across different tasks; finally, it proposes future research directions and suggests improvements in reproducibility and practical applications. By systematically summarizing algorithmic principles, experimental designs, and application scenarios, this paper strives to provide guidance for academic research and promote the efficient and reliable implementation of image enhancement technologies in real-world settings.

2. Deep Learning-Based Image Enhancement Model

2.1 Main Models of Image Enhancement

In the image enhancement section, the research focus lies on the effectiveness analysis of fully-supervised image enhancement based on Retinex theory. Retinex theory, grounded in a computational model of human perception of brightness and color, can simulate the imaging process of objects in the human eye, providing a theoretical foundation for image enhancement and making the enhanced images more aligned with human visual characteristics. In the deep learning section, denoising methods based on deep learning (such as DnCNN) are introduced to further improve image quality.

Fully-supervised image enhancement primarily comprises three stages: image decomposition, illumination enhancement, and color restoration with denoising. First, a deep convolutional network is employed to approximate image decomposition algorithms, providing feature support for subsequent enhancement. Second, an illumination enhancement network is utilized to improve the brightness and contrast of low-light images, making the images more recognizable [7]. However, compared to ground truth reference images, the enhancement results still exhibit certain issues of color distortion and noise. To address this, research further integrates 3D LUT with deep learning methods, overcoming the limitations of traditional 3D LUTs that rely on manual adjustment and fixed parameters, thereby achieving more flexible and automated image adjustments.

In the experimental analysis, variables related to the denoising module, illumination enhancement module, and color restoration module were controlled to compare the input images, intermediate results with specific modules

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omitted, final output images, and reference images. The results indicate that images lacking the denoising module exhibit significant noise, those without the illumination enhancement module appear overall dim, while images missing the color restoration module display over-saturated colors and excessively high contrast.

Additionally, this method was compared with classical algorithms such as CLAHE, MSRCR, and LIME. The results show that CLAHE has limited enhancement effectiveness on extremely low-light images, with insufficient brightness after enhancement; MSRCR generates images with significant noise; and LIME performs poorly in preserving edge details. In comparison, the proposed method demonstrates advantages in brightness, contrast, and detail preservation. However, it still falls short in fully aligning with human visual perception and leaves room for improvement when compared to high-quality reference images.

2.2 Analysis and Discussion

2.2.1 Computer vision model

lu Yuanyuan's team has established an image processing technology system that utilizes computer vision algorithms as the model and centers on deep learning [8]. The overall architecture comprises three main modules: image acquisition, processing, and display. The acquisition end relies on hardware such as cameras to capture images. The processing end proposes a deep learning algorithm based on CNNs, leveraging their characteristics of weight sharing and sparse connectivity to process images without secondary data extraction, thereby reducing model complexity. It also incorporates Sobel operator edge detection and Hough transform for auxiliary detection. The display end, centered around an ARM microprocessor, combines rapid projector projection and lateral transfer technology to achieve 3D image light field reconstruction, enhancing pixel density and resolution. To address image radial distortion, CNNs replace traditional methods to optimize the accuracy and efficiency of distortion correction, and a detection window image segmentation algorithm is designed to meet resolution requirements.

The aforementioned model features a simple structure, low cost, absence of visual interference, and supports human-computer interaction. It can be applied in scenarios such as face recognition and industrial screw defect detection, capable of efficiently processing various types of images while maintaining picture quality. However, the team applied the deep learning algorithm only to specific scenarios and did not present the image processing results, leading to insufficient model generalization capability and poor adaptability to other scenarios. Furthermore, the model faces a contradiction between hardware dependence and real-time performance: its reliance on a hardware combination of an ARM microprocessor, high-speed projector, and scattering screen for 3D display, while low-cost, may result in the ARM microprocessor's computing power being unable to support real-time inference of the CNN when processing high-frame-rate images, thus causing delays in image reconstruction and display.

To address these issues, it is recommended to integrate more models into the image enhancement technology. For instance, incorporating infrared image data could enhance reconstruction in low-light environments, and introducing LiDAR depth information during distortion correction could help preserve image authenticity, thereby expanding the model's application domains.

2.2.2 OpenCV image enhancement model

Sun Xiaokai's team conducted research focusing on an OpenCV-based image enhancement model, aiming to address the issue of scarce training data in deep learning image recognition [9]. The model design included four sets of controlled experiments: V1 used only real images, V2 used enhanced images with plain backgrounds, V3 used enhanced images with complex backgrounds, and V4 used 50% real images combined with 50% enhanced images with complex backgrounds. All experiments were conducted on 10 categories of items, trained and tested under a unified recognition algorithm and test set. The results showed that V1 achieved the highest mean average precision at 97.2%; V4 reached 96.6%, close to V1 and even outperforming it in certain categories (e.g., dice); while V2 and V3 only achieved 73.68% and 81.5%, respectively. The conclusion was that enhancement alone has limited effectiveness and must be combined with real data; this model can improve recognition performance with small-scale data, reduce data costs, and is suitable for customized recognition scenarios.

A key limitation lies in the lack of diversity in data augmentation. The aforementioned study only performed operations such as flipping and background replacement on single original images, which essentially constitutes repetitive transformations of the same object instance's features without introducing other object instances. As a result, the model can only recognize trained instance variations and struggles to generalize to other real-world objects of the same category. To address this issue, it is recommended to incorporate more diverse samples during model training, such as objects of different sizes, brands, and colors, to enhance data variety. Additionally, differentiated enhancement strategies could be designed for different instances: applying more lighting and angle variations for objects with simple features, while focusing on preserving key details for objects with complex features, thereby improving the model's generalization capability.

2.2.3 YOLOv3 model

Sun Dongyang's team conducted research on deep learning-based image classification and target detection of underwater organisms in marine ranches [10]. They established a classification dataset containing 22,311 images of 15 species (11 fish species, 3 echinoderm species, and 1 crab species), and a detection dataset with 6,405 labeled instances of 12 rocky reef fish species. By comparing three classification networks-AlexNet, MobileNetV3, and ResNet50-they found that ResNet50 demonstrated the best robustness on images with Gaussian noise, achieving a class accuracy of 99.23% on the test set. For target detection, the YOLOv3 model based on Darknet-53 was used, and after parameter tuning, it reached a mAP of 81.38%, providing technical support for intelligent monitoring of biological communities in marine ranches.

A limitation of the study is that the dataset used only covers northern sea areas, with backgrounds limited to three types: artificial reefs, algal beds, and sediment, without including species from other sea areas or different environmental factors. Although the YOLOv3 model improves the detection capability for small targets through multi-scale detection, experimental results still reveal two issues: first, a high missed detection rate for small targets such as juvenile fish and small echinoderms; second, difficulty in effectively distinguishing individual outlines in cases of overlapping organisms or fish aggregations, leading to overlapping or missing bounding boxes. To address the aforementioned issues, it is recommended to expand the monitoring range to more sea areas and perform separate detection on overlapping biological samples to improve the model's recognition accuracy and applicability.

3. Summary

This study systematically analyzes deep learning-based image enhancement techniques and their applications in typical tasks. The results demonstrate that image enhancement can effectively improve the recognizability of low-quality images, showing significant application value in fields such as low-light environments, medical imaging, and satellite remote sensing. Compared to traditional methods reliant on manual adjustment, deep learning approaches exhibit clear advantages in reducing labor costs, improving model generalization capability, and enhancing image quality. However, existing methods still face challenges including color distortion, inadequate detail restoration, high computational costs, and strong dependence on specific datasets. Furthermore, some models overlook the authentic visual perception of the human eye during the optimization process, leaving room for improvement in image realism and natural appearance. Additionally, current research generally lacks testing in real-world scenarios, with some datasets suffering from geographical limitations and uneven sample distribution. The adaptability of algorithms across diverse target types also requires further enhancement. Future work should focus on supplementing real-world experiments, expanding the geographical coverage and sample diversity of datasets, and optimizing algorithm structures for different objects, thereby improving the adaptability and robustness of image enhancement techniques across multiple scenarios. Future research should prioritize directions such as lightweight model design, preservation of visual authenticity, and the integration of multiple technologies to enhance the practicality and generalization performance of the algorithms.

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