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Low Light Image Enhancement

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ABSTRACT: This project presents a novel method for improving the quality of roadside photos taken at night, which is essential for intelligent transportation systems. The current techniques for enhancing low-light images frequently lead to colour irregularities and other problems. The approach uses a variety of sensors and methods to address these issues. We improve images using a unique technique termed bidirectional area segmentation based inverse tone mapping in place of traditional techniques. Additionally, use a special highlighting technique based on accurate identification of moving objects in the image data to address the issue of moving objects seeming dull. Ultimately, use a pyramid-based fusion technique to produce high-quality traffic photographs. Experiments using a range of photos show that our method works better than current approaches in terms of improving image details and producing more realistic colours for better human perception.

KEYWORDS: Low-Light Image Enhancement, Intelligent Transportation Systems(ITS),Bidirectional Area Segmentation, Inverse Tone Mapping, Pyramid-Based Fusion, Multi-Sensor Data Fusion

I. INTRODUCTION

Collaborative Autonomous vehicles, intelligent infrastructure, and traffic control centres can collaborate and communicate thanks to Intelligent Transport Systems (sometimes referred to as Cooperative ITS or C-ITS), also known as vehicle-road cooperation systems or vehicle-road collaboration systems. The Internet of Things (IoT), smart cities, and driverless cars have all been made possible by C-ITS. The computer vision-based roadside occupancy surveillance system, also known as the roadside utils or RSU, is one of the most valued technologies in C-ITS. Compared to vehicle sensors, it offers greater traffic information dimensions and longer coverage. The C-ITS has effectively implemented RSU due to its easy-to-use interface and flexible deployment. However, vision-based roadside utilities frequently perform poorly or even fail to function at night due to low visibility and unexpected noise in traffic photos taken in low light. All of these events highlight the urgent need for answers to the issues of declining image quality. While several of the current image enhancement methods, such wavelet decomposition, histogram enhancement, and the retinex algorithm, have shown promising results in some scenarios and data sets, they are frequently unreliable and wasteful in real-world traffic applications. One of the main causes is that the colour and detail degradation of nighttime photos taken by inexpensive traffic cameras might occasionally be too severe to satisfy the requirements for the single-frame image improvement mentioned above. Additionally, after being properly taught, certain deep learning-based image enhancing techniques, such Dual-Channel Dehazine-Net, can perform better. It can be difficult to get accurate training data in practical engineering, though. Context enhancement-based methods, such multi sensor fusion (MSF) and multi exposure fusion (MEF), have been extensively employed in C-ITS to address the aforementioned problems. The quality of the deteriorated photos taken at night or in low light conditions can be improved by using several information dimensions, satisfying the needs of intelligent applications. This work uses multi-source data fusion to offer a new pseudo-multi-exposure fusion-based picture improvement technique for low-light traffic photographs. Through pixel-level fusion of day and night photos and decision-level fusion of camera and radar, our approach may greatly increase the texture of important traffic participants and improve the quality of nighttime photographs.

II. LITERATURE SURVEY

G. Sahu et. al(2022)For the last two decades, image processing techniques have been used frequently in computer vision applications. The most challenging task in image processing is restoring images that are degraded due to various weather conditions. Mainly, the visibility of outdoor images is corrupted due to adverse atmospheric effects. The visibility of acquired images is reduced in these circumstances. Haze is an atmospheric phenomenon that reduces the clarity of an image. Due to the presence of particles such as dust, dirt, soot, or smoke, there is significant decay in the colour and contrast of captured images. Haze present in acquired images causes issues in a variety of computer vision applications. Therefore, enhancing the contrast of a hazy image and restoring the visibility of the scene is essential. Since clear images are required in every application, image dehazing is an important step. Hence, many researchers are working on it. Different methods have been presented in the literature for image dehazing. This study describes various traditional and deep learning techniques of image dehazing from an analytical perspective. The main intention behind this work is to provide an intuitive understanding of the major techniques that have made a relevant contribution to haze removal. In this paper, we have covered different types of contributions toward dehazing based on the traditional method as well as deep learning approaches. With a considerable amount of instinctive simplifications, the reader is expected to have an improved ability to visualize the internal dynamics of these processes.

P. Liu et. al(2022)Roadside object detection and classification provide a good understanding of driving scenarios in regard to over-the-horizon perception. However, typical roadside sensors are insufficient when used separately. The fusion of the millimeter-wave (MMW) radar and monovision camera serves as an efficient approach. Unfortunately, the uncertain and conflicting data in extreme light conditions pose challenges to the fusion process. To this end, this study proposed an evidential framework to fuse the radar and camera data. A novel modeling approach for basic belief assignments (BBAs) was proposed, which took the uncertainty of convolutional neural network (CNN) model into consideration. Moreover, the single-scan and multiscan fusion methods were developed based on the enhanced evidence theory, which utilized different weighted coefficients by referring to the reinforced belief (RB) divergence measure and belief entropy (BE). Both numerical and empirical experiments were conducted to investigate the method performance. Specifically, in numerical experiments, the belief value of actual classification increased to 99.01%. For empirical experiments, based on the real datasets collected by roadside devices, the proposed method was demonstrated to outperform the state-of-the-art ones in terms of 71.06% and 87.23% precisions for bright light and low illumination conditions, respectively. The results verify that the proposed method is effective in fusing the conflicting and uncertain data

F. Xu et. al(2022)Multi-exposure image fusion (MEF) is emerging as a research hotspot in the fields of image processing and computer vision, which can integrate images with multiple exposure levels into a full exposure image of high quality. It is an economical and effective way to improve the dynamic range of the imaging system and has broad application prospects. In recent years, with the further development of image representation theories such as multi-scale analysis and deep learning, significant progress has been achieved in this field. This paper comprehensively investigates the current research status of MEF methods. The relevant theories and key technologies for constructing MEF models are analyzed and categorized. The representative MEF methods in each category are introduced and summarized. Then, based on the multi-exposure image sequences in static and dynamic scenes, we present a comparative study for 18 representative MEF approaches using nine commonly used objective fusion metrics. Finally, the key issues of current MEF research are discussed, and a development trend for future research is put forward.

X. H. Xu K, Wang Q (2022)High-dynamic-range (HDR) image has a wide range of applications, but its access is limited. Multi-exposure image fusion techniques have been widely concerned because they can obtain images similar to HDR images. In order to solve the detail loss of multi-exposure image fusion (MEF) in image reconstruction process, exposure moderate evaluation and relative brightness are used as joint weight functions. On the basis of the existing Laplacian pyramid fusion algorithm, the improved weight function can capture the more accurate image details, thereby making the fused image more detailed. In 20 sets of multi-exposure image sequences, six multi exposure image fusion methods are compared in both subjective and objective aspects. Both qualitative and quantitative performance analysis of experimental results confirm that the proposed multi-scale decomposition image fusion method can produce high-quality HDR images.

X. Wang et.al(2022)Inspired by image-to-curve transformation and multi-exposure fusion, in this paper, we have developed a new method to treat the low light image enhancement tasks as an extended problem with multiple virtual exposures by a non-linear intensity mapping function. Considering that existing image-to-curve methods have difficulty in obtaining the desired detail and brightness recovery in any one iteration without relying on any ground truth, we propose a virtual multi exposure fusion strategy to merge the outputs from these different iterations. Specifically, a simple CNN is trained to learn a pixel-wise intensity mapping function and accordingly adjust a given image multiple times. Then the results of all iterations are retained together with the original input image for fusion via a WGIF-based Multi-scale pyramid to obtain a final enhanced output. We present experimental results to demonstrate the effectiveness of the new technique and its state-of-the-art performances.

Existing System

The conventional approach to enhancing nighttime roadside photos in the existing system frequently involves crudely segmenting the image into moving and stationary regions using radar detection data. Less than ideal improvement could result from this straightforward method's inability to handle the complexities of low-light conditions. Moreover,

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the exposure fusion algorithms employed in existing systems might not fully capture the intricate relationship between low-light and reference photos. As a result, the generated photos may only..show..slight..improvements..in..contrast,..detail,..and..colour..realism.

Disadvantages

1. It's frequently difficult to capture the intricate mapping relationship between reference and low-light photos.
2. It could be challenging to synchronize contrast enhancement and gradient-domain reconstruction, leading to less coherent and realistic results
3. It could be challenging to accurately recognize and highlight specific regions in the night time roadside photos.

Proposed System

Advantages

- Enabling a more comprehensive and accurate representation of the characteristics of low-light photos.
- Ensuring accurate and useful enhancements.
- Providing a nighttime roadside landscape that is more authentic and visually appealing

System Architecture

The system architecture for low light image enhancement can be summarized as follows:

1. Input Image: A low-light image with issues like low brightness, noise, and poor contrast.
2. Preprocessing:
   - Denoising: Reduce noise using methods like Gaussian blur or wavelet denoising.
   - Colour Correction: Adjust colour balance and saturation.
   - Normalization: Standardize pixel values for better processing.
3. Illumination Estimation:
   - Estimate scene illumination to adjust dynamic range and contrast, using methods like dark channel prior or adaptive histogram equalization.
4. Image Enhancement:
   - Histogram Equalization: Enhance global and local contrast.
   - Retinex-based Methods: Separate and enhance illumination and reflectance for better details.
   - Deep Learning: Apply CNNs or GANs for advanced enhancement.
5. Post-Processing:
   - Edge Enhancement: Sharpen details and highlight features.
   - Noise Reduction: Apply additional filtering to reduce noise.
   - Saturation Adjustment: Improve colour saturation for better image quality.
6. Output Image: A high-quality, enhanced image with improved brightness, contrast, and details, suitable for further analysis or visualization.

This architecture aims to improve the visibility and quality of low-light images by addressing brightness, contrast, and noise issues through various techniques, including traditional algorithms and deep learning models.

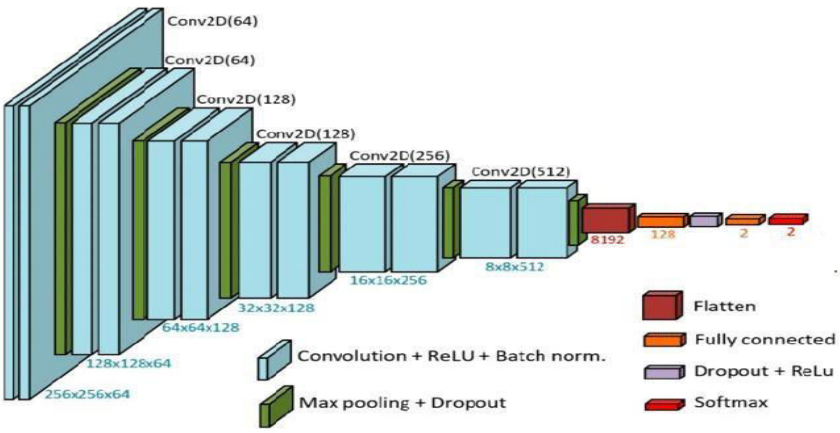

Figure 1:SYSTEM ARCHITECTURE

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III. METHODOLOGY

Low image enhancement describes methods for enhancing low contrast or deteriorated photographs, which are frequently brought on by blurriness, noise, or inadequate lighting. This field uses a variety of approaches, which fall into the following categories:

1. **Methods Based on Histograms**

Equalization of Histograms (HE): Using this method, the intensity levels of the pixels in the images are redistributed throughout the whole ranges. By making the image seem crisper, it enhances the contrast.

2. **Methods Based on Retinex**.

Based on the Retinex theory, these techniques seek to distinguish between the image's illumination and reflectance components. Improving the reflectance, which includes object features, enhances image quality, particularly in different lighting situations

Modules:-

1.Image..Collection

The process of compiling a wide range of visual content for use in both professional and personal contexts is known as image collection. It entails locating, classifying, and selecting photos from a variety of sources, including social mediaplatforms, stock photo collections, photography websites,andindividual typephotography .The gathered photos might be used for research projects, marketing campaigns, instructional materials, artistic pursuits, or just for personal records

2. CNN+Pyramid Model:

Convolutional Neural Network with Pyramid architecture, or CNN+ Pyramid model, is a deep learning architecture intended for applications like object detection and picture recognition. It combines the multi-scale feature representation offered by pyramid structures with the advantages of convolutional neural networks (CNNs). The CNN component of this model uses convolutional layers to extract features at various levels of abstraction while processing input images hierarchically.

3.Image..Segmentation

A basic task in computer vision is image segmentation, which is dividing an image into several segments or regions according to specific attributes, including colour, texture, or intensity, in order to simplify picture representation and extract useful information. Segmenting a picture into semantically relevant portions is the primary goal of image segmentation, which makes it possible to analyze, comprehend, and manipulate visual content more effectively.

Implementation

Algorithm:

1.Histogram..Equalization

GHE, or global histogram equalization: To increase contrast, this technique re-distributes pixel intensity throughout the image. It might, however, result in some parts of the image being unnaturally enhanced.

2. Retinex Theory

Retinex algorithms distinguish between an image's light and reflectance components by simulating human vision. By increasing the reflectance component, these methods make dark parts more visible without overexposing bright ones.

3.Gamma..Correction

Gamma correction modifies an image's contrast and brightness. By altering the image's gamma value, a gamma correction can boost brightness in low-light situations, where an image usually appears dark.

4.De-noising

Noise is a common problem with low-light photos, particularly in areas with extremely low illumination levels. While maintaining crucial visual information, denoising algorithms aid in the removal of this noise.

5. Brightness and Contrast Adjustment

Certain algorithms use pixel-by-pixel operations to directly improve brightness or modify contrast. To increase their visibility, this may entail increasing the lower-end pixel intensities, or the dark regions.

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Experiment Results

INPUT 1

OUTPUT 1

INPUT 2

OUTPUT 2

IV. CONCLUSION

We provide an effective flowchart for night image enhancement using multi-source data fusion to support multi-object identification and recognition tasks on the Intelligent Roadside Surveillance System. We provide a full set of multi-sensor fusion algorithms appropriate for the intelligent roadside system, using a fixed field of view and simple multi-sensor fusion. The pixel-level fusion of day and night images and the decision-level fusion of camera and radar are the two main fusions.

V. FUTURE ENHANCEMENT

To further increase the quality of nighttime roadside images for intelligent transportation systems, this project could be expanded and improved in a number of ways in the future. To improve image quality and preserve natural colour representation, one possible option for improvement would be to refine and optimize the suggested bidirectional area segmentation based inverse tone mapping technique. Furthermore, additional research might concentrate on improving the highlighting process for moving objects, possibly implementing sophisticated motion tracking algorithms or machine learning strategies for more precise highlighting and identification. The effectiveness of the pyramid-based fusion approach could be increased in the future by investigating additional sensor technologies or data fusion strategies, which would allow for the creation of even higher-quality images**.**

REFERENCES

1. P. D. Macheret, R. Savchuk, and G. Shkuratov, “Intelligent transport systems: Analysis of the current state and prospects of development,” 2021 International Conference on Quality Management, Transport and Information Security, Information Technologies, 2021.
2. J. Mao, D. Hong, X. Wang, C. H. Hsu, and A. Shanthini, “Cvrrss-chd: Computer vision related roadside surveillance system using compound hierarchical-deep models,” IET Intelligent Transport Systems, vol. 14, no. 11, pp. 1353–1362, 2020.

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3. S. T. T and S. M., “Nighttime visual refinement techniques for surveillance video: a review,” p. 32137-32158, 2019.
4. G. Sahu, A. Seal, D. Bhattacharjee, M. Nasipuri, P. Brida, and O. Krejcar, “Trends and prospects of techniques for haze removal from degraded images: A survey,” IEEE Transactions on Emerging Topics in Computational Intelligence, vol. 6, no. 4, pp. 762–782, 2022.
5. G. Sahu, A. Seal, O. Krejcar, and A. Yazidi, “Single image dehazing using a new colour channel,” Journal of Visual Communication and Image Representation, vol. 74, p. 103008, 2021.
6. G. Sahu, A. Seal, A. Yazidi, and O. Krejcar, “A dual-channel dehazenet for single image dehazing in visual internet of things using pynq-z2 board,” IEEE Transactions on Automation Science and Engineering, pp. 1–15, 2022.
7. J. Bai, S. Li, L. Huang, and H. Chen, “Robust detection and tracking method for moving object based on radar and camera data fusion,” IEEE Sensors Journal, vol. PP, no. 99, pp. 1–1, 2021.
8. P. Liu, G. Yu, Z. Wang, B. Zhou, and P. Chen, “Object classification based on enhanced evidence theory: Radar-vision fusion approach for roadside application,” IEEE Transactions on Instrumentation and Measurement, vol. 71, pp. 1–12, 2022.
9. M. Gao, J. Wang, Y. Chen, C. Du, and Y. Zeng, “An improved multiexposure image fusion method for intelligent transportation system,” Electronics, vol. 10, no. 4, p. 383, 2021.
10. M. Bouain, D. Berdjag, N. Fakhfakh, and R. B. Atitallah, “Multi-sensor fusion for obstacle detection and recognition: A belief-based approach,” in 2018 21st International Conference on Information Fusion (FUSION), 2018, pp. 1217–1224.
11. Y. Li, M. Liu, and K. Han, “Overview of multi-exposure image fusion,” in 2021
12. International Conference on Electronic Communications, Internet of Things and Big Data (ICEIB), 2021, pp. 196–198.
13. Y. Liu, L. Wang, J. Cheng, C. Li, and X. Chen, “Multi-focus image fusion: A survey of the state of the art,” Information Fusion, vol. 64, pp. 71–91, 2020.
14. F. Xu, J. Liu, Y. Song, H. Sun, and X. Wang, “Multi-exposure image fusion techniques: A comprehensive review,” Remote Sensing, vol. 14, 2022.
15. X. H. Xu K, Wang Q and L. K, “Multi-exposure image fusion algorithm based on improved weight function,” Neurorobot, 2022.
16. Z. Yang, Y. Chen, Z. Le, and Y. Ma, “Ganfuse: a novel multi-exposure image fusion method based on generative adversarial networks,” Neural Computing and Applications, vol. 33, pp. 6133–6145, 2021.
17. O. Ulucan, D. Karakaya, and M. Turkan, “Multi-exposure image fusion based on linear embeddings and watershed masking,” Signal Processing, vol. 178, p. 107791, 2021.
18. K. R. Prabhakar, V. S. Srikar, and R. V. Babu, “Deepfuse: A deep unsupervised approach for exposure fusion with extreme exposure image pairs,” 2017 IEEE International Conference on Computer Vision (ICCV), 2017.
19. S. Sen Gupta, S. Hossain, and K.-D. Kim, “Hdr-like image from pseudoexposure image fusion: A genetic algorithm approach,” IEEE Transactions on Consumer Electronics, vol. 67, no. 2, pp. 119–128, 2021.
20. Y. Kinoshita, T. Yoshida, S. Shiota, and H. Kiya, “Pseudo multi-exposure fusion using a single image,” in 2017 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC), 2017.
21. T. H. Wang, C. W. Chiu, W. C. Wu, J. W. Wang, C. Y. Lin, C. T. Chiu, and J. J. Liou, “Pseudo-multiple-exposure-based tone fusion with local region adjustment,” IEEE Transactions on Multimedia, vol. 17, no. 4, pp. 470– 484, 2015.
22. X. Wang, R. Hu, and X. Xu, “Single low-light image brightening using learning-based intensity mapping,” Neurocomputing, vol. 508, pp. 315– 323, 2022.
23. H. Dong, K. Song, Y. He, J. Xu, Y. Yan, and Q. Meng, “Pga-net: Pyramid feature fusion and global context attention network for automated surface defect detection,” IEEE Transactions on Industrial Informatics, vol. 16, no. 12, pp. 7448–7458, 2020.
24. D. Liu, Y. Cui, L. Yan, C. Mousas, and Y. Chen, “Densernet: Weakly supervised visual localization using multi-scale feature aggregation,” in The Thirty-Fifth AAAI Conference on Artificial Intelligence (AAAI-21), 2020.
25. M. Zhang, T. Liu, Y. Piao, S. Yao, and H. Lu, “Auto-msfnet: Search multi-scale fusion network for salient object detection,” in The 29th ACM international conference on multimedia, 2021.
26. S. Feng, H. Zhao, F. Shi, X. Cheng, M. Wang, Y. Ma, D. Xiang, W. Zhu, and X. Chen, “Cpfnet: Context pyramid fusion network for medical image segmentation,” IEEE Transactions on Medical Imaging, vol. 39, no. 10, pp. 3008–3018, 2020.
27. K. R. Prabhakar and R. V. Babu, “Ghosting-free multi-exposure image fusion in gradient domain,” in 2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2016.
28. F. Vasconcelos, J. P. Barreto, and U. Nunes, “A minimal solution for the extrinsic calibration of a camera and a laser-rangefinder,” IEEE Transactions on Software Engineering, vol. 34, no. 11, 2012.

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29. E. Reinhard, M. Ashikhmin, B. Gooch, and P. Shirley, “Color transfer between images,” IEEE Computer Graphics and Applications, vol. 21, no. 5, pp. 34–41, 2002.
30. M. F. Al-Sammaraie, “Contrast enhancement of roads images with foggy scenes based on histogram equalization,” in International Conference on Computer Science and Education, 2015. [30] G. Sahu and A. Seal, “Image dehazing based on luminance stretching,” in 2019 International Conference on Information Technology (ICIT), 2019, pp. 388–393.
31. A. Mgg, A. Kts, and B. Gsa, “Image dehazing using msrcr algorithm and morphology based algorithm : A concise review - sciencedirect,” Materials today: proceedings, 2020.
32. K. F. Yang, H. Li, H. Kuang, C. Y. Li, and Y. J. Li, “An adaptive method for image dynamic range adjustment,” IEEE Transactions on Circuits and Systems for Video Technology, pp. 1–1, 2018.
33. X. Ye, M. Shu, H. Li, Y. Shi, Y. Li, G. Wang, X. Tan, and E. Ding, “Rope3d: Theroadside perception dataset for autonomous driving and monocular 3d object detection task,” 2022.
34. A. Tavakkoli, M. Nicolescu, and G. Bebis, “Automatic robust background modeling using multivariate non-parametric kernel density estimation for visual surveillance,” in IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2005, p. 246-252.
35. G. Qu, D. Zhang, and P. Yan, “Information measure for performance of image fusion,” Electronics Letters, vol. 38, no. 7, pp. 313–315, 2002.
36. S. S. Agaian, K. P. Lentz, and A. M. Grigoryan, “A new measure of image enhancement,” in the IASTED Int. Conf. Signal Processing Communication, 2000, p. 19-22.
37. G. Sharma, W. Wu, and E. N. Dalal, “The ciede2000 colour-difference formula: Implementation notes, supplementary test data, and mathematical observations,” Colour Research and Application, vol. 30, pp. 21–30, 2010.
38. R. Mantiuk, K. J. Kim, A. G. Rempel, and W. Heidrich, “Hdr-vdp2: a calibrated visualmetric for visibility and quality predictions in all luminance conditions,” Acm Transactions on Graphics, vol. 30, no. 4, pp. 1–14, 2011.
39. A. Mittal and A. K. Moorthy, “Blind/referenceless image spatial quality evaluator,” in Signals, Systems and Computers, 2012.[40] M. Aeberhard and T. Bertram, “Object classification in a high-level sensor data fusion architecture for advanced driver assistance systems,” in 2015
IEEE 18th International Conference on Intelligent Transportation Systems, 2015, pp. 416–422.

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