e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:06/Issue:12/December-2024 Impact Factor- 8.187 www.irjmets.com

LOW LIGHT IMAGE ENHANCEMENT

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ABSTRACT

Low-light environments often degrade image quality, posing challenges in applications like surveillance and autonomous driving. This paper presents a novel approach combining Convolutional Neural Networks (CNN) with a pyramid-based fusion technique to enhance low-light images. Our method leverages deep learning for feature extraction and multi-scale fusion to preserve fine details and improve illumination. Comparative experiments demonstrate superior performance over existing state-of-the-art methods.. This research introduces an innovative approach to enhance the quality of nighttime roadside images, crucial for intelligent transportation systems. Current methods for improving low-light photos often result in color abnormalities and other issues. Our solution addresses these challenges by incorporating multiple sensors and techniques. Instead of conventional methods, we utilize a novel approach called bidirectional area segmentation-based inverse tone mapping to enhance photos. Additionally, we tackle the problem of moving objects appearing dim by employing a unique highlighting method based on precise identification of moving objects in the image data. Ultimately, we generate high-quality traffic photos using a pyramid-based fusion approach. Experiments with various images demonstrate that our technique outperforms existing methods in enhancing image details and creating more realistic colors for improved human observation.

Keywords: CNN, Pyramid-Based Fusion Technique, Low-Light Photos, Bidirectional Area Segmentation.

I. INTRODUCTION

Cooperative Intelligent Transport Systems (Cooperative ITS or C-ITS), also known as vehicle-road cooperation systems and vehicle-road collaboration systems, enable cooperation and communication between autonomous vehicles, intelligent infrastructure, and traffic control centers. C-ITS has been the driving force to enable autonomous vehicles, smart cities, and the Internet of Things (IoT). As one of the most valued technologies in C-ITS, the Computer Vision Based roadside occupation surveillance system (Roadside utils or RSU) provides extended coverage and more traffic information dimensions than vehicle sensors. With the flexible deployment and ease of operation, RSU has successfully been applied in the C-ITS . However, Traffic images captured under low-light conditions suffer from low visibility and unexpected noise, and therefore Vision-Based roadside utils often work inefficiently or even fail to operate at night. All these phenomena urge a vigorous need for solutions to address image quality degradation problems. Although some existing image enhancement algorithms, such as histogram enhancement, Retinex algorithm, and wavelet decomposition, have achieved good results in data sets and some specific scenarios these are often inefficient and unstable in practical traffic application. One of the most important reasons is that the details and color degradation of night images captured by low-cost traffic cameras are sometimes too serious about meeting the preconditions for the above single-frame image enhancement. Besides, some deep learning-based image enhancement methods can achieve better performance after being properly trained, such as Dual-Channel Dehazine-Net. However, obtaining proper training data in practical engineering is challenging. To overcome the above issues, context enhancementbased techniques, such as multi-sensor fusion (MSF) and multiexposure fusion (MEF), have been widely used in C-ITS. Using various dimensions of information can improve the quality of the degraded images captured under poor illumination or nighttime, thus meeting the requirements of intelligent applications. This paper proposes a novel pseudo-multi-exposure fusion-based image enhancement algorithm for low-light traffic images via multi-source data fusion. By the decision level fusion of camera and radar and pixel level fusion of day image and night image, our method can improve the quality of the nighttime images and significantly enhance the texture of key traffic participants such as vehicles and pedestrians. The suggested method is extensively evaluated on the Rope3D dataset and nighttime images captured by an Intelligent Roadside Surveillance System, demonstrating the effectiveness and generalization of our approach. Fig. 1 depicts some examples from the proposed method. This paper's contributions are as follows: • A novel night color image enhancement approach is introduced by combining multi-sensor and pseudo-multiexposure fusion techniques. • A region-based tone mapping method is proposed to generate the multi-exposure sequence from day and night image pairs. • The data from the radar sensors are exploited to generate moving regions in the image, and a PDE-based luminance stretching is further applied to these areas to highlight the traffic targets. • An improved weighting function for the pyramid fusion is used to generate high-quality traffic images. Specifically, we consider guidance information in the weight calculation process. The remainder of this paper is organized as follows. Section 2 reviews the related works about MEF. Section 3 proposes a novel Pseudo Multi-Exposure Fusion-based image enhancement algorithm for traffic low-light images is proposed via multi-source data fusion. Section 4 discusses the experimental results, and finally, Section 5 concludes this paper and suggests some future research directions.

II. RELATED WORK

The scope of this project encompasses the development and implementation of an innovative approach to enhance the quality of nighttime roadside images, crucial for intelligent transportation systems. The focus lies on addressing the limitations of existing methods for improving low-light photos, such as color abnormalities and inadequate representation of moving objects. The project aims to introduce a novel technique called bidirectional area segmentation based inverse tone mapping, which preserves natural color representation while enhancing overall image quality. Additionally, the project includes the implementation of a unique highlighting method based on precise identification of moving objects within the image data to mitigate the issue of dimly lit objects.

The objective of this project is to develop and implement an innovative approach to enhance the quality of nighttime roadside images, particularly for applications in intelligent transportation systems. This involves addressing the limitations of existing methods for improving low-light photos, such as color abnormalities and inadequate representation of moving objects. The specific goals include introducing a novel technique called bidirectional area segmentation-based inverse tone mapping to maintain natural color representation while enhancing overall image quality. Additionally, the project aims to devise a unique highlighting method based on precise identification of moving objects within the image data to alleviate the issue of dimly lit objects.

The traditional method of improving roadside images at night in the current system often entails dividing the image into moving and stationary areas using radar detection data in a crude manner. This simplistic approach could not be sophisticated enough to handle the intricacies of low-light situations, leading to less than ideal improvement. Moreover, the complex interaction between low-light and reference photos may not be adequately captured by the exposure fusion algorithms used in current systems. Consequently, only minimal increases in contrast, detail, and color realism may be seen in the produced images. Frequently fall short in accurately portraying the complex mapping connection between reference and low-light images. May find it difficult to coordinate gradient-domain reconstruction with contrast enhancement, producing improvements that are less realistic and cohesive. Might find it difficult to precisely identify and enhance certain areas in the roadside images taken at night.

III. SURVEY WORKS

G. Sahu, A. Seal, D. Bhattacharjee, M. Nasipuri, P. Brida, and O. Krejcar, 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 color 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

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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, G. Yu, Z. Wang, B. Zhou, and P. Chen, 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-ofthe-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, J. Liu, Y. Song, H. Sun, and X. Wang, 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 and L. K, 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, R. Hu, and X. Xu, 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 multiexposure 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.

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IV. PROPOSED WORK

We present a novel approach to nighttime roadside picture augmentation that makes use of a bespoke Convolutional Neural Network (CNN). For the purpose of analyzing low-light pictures in intelligent transportation systems, CNN was particularly created. Our approach seeks to address color anomalies and other problems common to existing enhancement techniques by integrating many sensors and cutting-edge algorithms. Our system's bespoke CNN makes use of a cutting-edge method known as bidirectional area segmentation-based inverse tone mapping. The quality of images taken in low light is greatly enhanced by this novel technique, which substitutes traditional ones. The frequent problem of moving objects seeming faint in the pictures is also covered by CNN. This is accomplished by applying a particular highlighting technique that is predicated on accurately identifying moving objects in the picture data. This guarantees that realistic colors and precise details are maintained in the improved images.

This paper aims to revolutionize the enhancement of nighttime roadside images, a critical aspect for intelligent transportation systems. Current methods often fall short due to issues like color aberrations and poor representation of moving objects. To address these challenges, we propose an innovative approach centered around bidirectional area segmentation-based inverse tone mapping, which preserves natural color fidelity while enhancing overall image quality. Additionally, we introduce a novel highlighting method based on precise identification of moving objects within the image data to combat the problem of dimly lit objects. Our methodology also includes a pyramid-based fusion approach, leveraging information from multiple sensors and techniques to generate high-quality traffic photos. Through extensive experimentation with diverse image datasets, we aim to demonstrate the superiority of our technique in enhancing image details and producing more realistic colors, ultimately contributing to significant advancements in intelligent transportation systems.

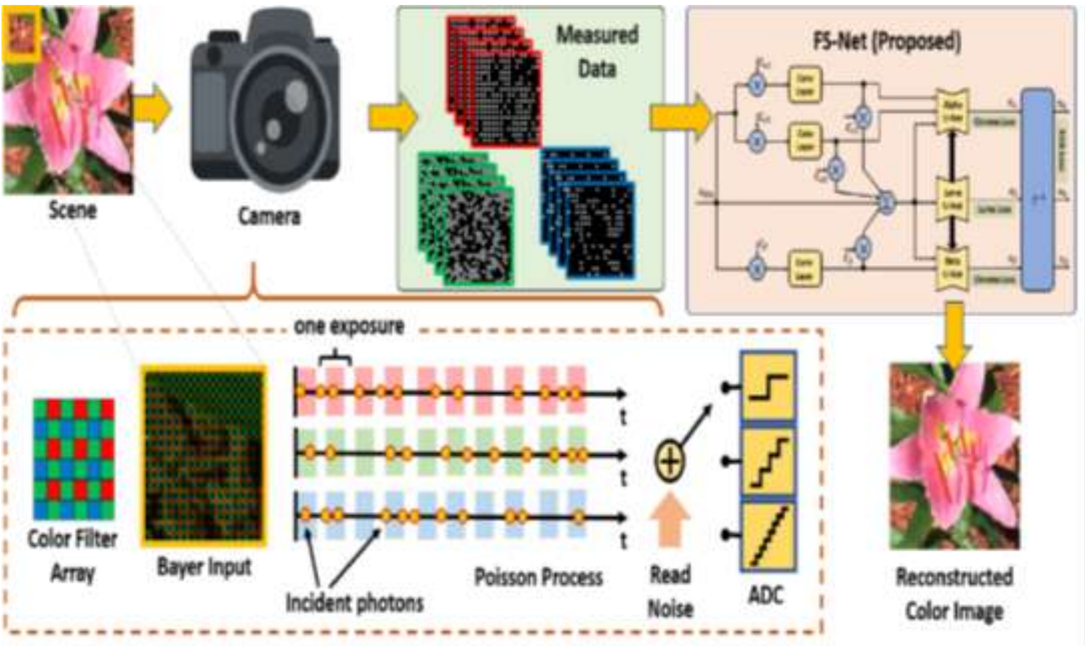

Fig 1:

1) Image Collection:

Image collection is the process of gathering a diverse array of visual content for various purposes, ranging from personal enjoyment to professional use. It involves sourcing, organizing, and curating images from different sources such as photography websites, stock photo libraries, social media platforms, and personal photography. The collected images may be used for artistic projects, marketing materials, educational resources, research endeavors, or simply for personal documentation.

2) CNN+Pyramid Model:

The CNN+Pyramid model, also known as Convolutional Neural Network with Pyramid architecture, is a deep learning architecture designed for tasks such as image recognition and object detection. It combines the

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strengths of convolutional neural networks (CNNs) with the multi-scale feature representation provided by pyramid structures. In this model, the CNN component processes input images hierarchically, extracting features at multiple levels of abstraction through convolutional layers.

3) Image Segmentation:

Image segmentation is a fundamental task in computer vision that involves partitioning an image into multiple segments or regions based on certain characteristics, such as color, texture, or intensity, with the goal of simplifying the representation of an image and extracting meaningful information. The main objective of image segmentation is to divide an image into semantically meaningful parts, enabling more efficient analysis, understanding, and manipulation of visual content.

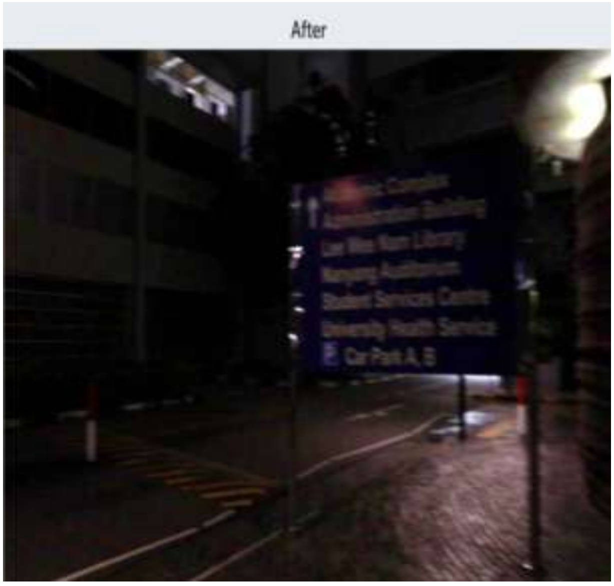

Fig 2: Enhances the objects within the image

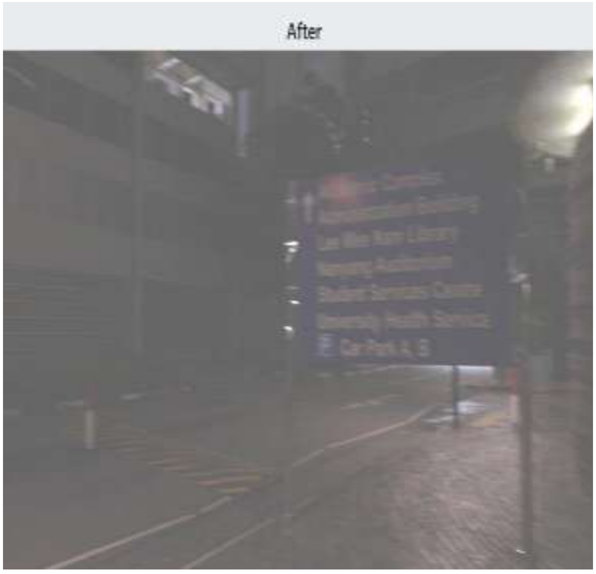

Fig 3: Outer layer on the Image

Fig 4: A technique that adjusts the pixel values of an image based on its intensity histogram.

Fig 5: Technique for identifying and locating the boundaries or edges of image.

4) Histogram Analysis:

Histogram analysis is a fundamental technique in image processing and computer vision that involves analyzing the distribution of pixel intensities within an image. A histogram is a graphical representation of the frequency of occurrence of each intensity value in the image, with darker pixels represented on the left and brighter pixels on the right. By examining the shape and characteristics of the histogram, valuable insights can be gained about the overall brightness, contrast, and distribution of tones within the image.

5) Image Processing:

Image processing refers to the manipulation and analysis of digital images to extract useful information, enhance visual quality, or perform specific tasks for various applications. It encompasses a wide range of techniques and algorithms aimed at modifying images to achieve desired objectives. Basic image processing operations include resizing, cropping, and rotating images, which are commonly used for tasks such as preparing images for display or fitting them into specific dimensions. More advanced image processing techniques involve filtering, which modifies pixel values based on local neighborhoods to remove noise, enhance details, or highlight specific features.

6) Image Enhancement:

Image enhancement is a fundamental process in image processing that aims to improve the visual quality of digital images by emphasizing certain features, reducing noise, enhancing contrast, or adjusting brightness and color balance. It encompasses a variety of techniques and algorithms designed to enhance specific aspects of an image while preserving its overall integrity and fidelity. Basic image enhancement operations include brightness and contrast adjustment, which modify the intensity levels of pixels to make the image appear brighter or darker and enhance the overall contrast between different regions.

Our solution uses Flask for manual picture entry in order to create an interface that is easy for users to use. This web framework makes interaction fluid and makes it simple for users to submit and edit photographs taken at night from the side of the road. Our image improvement system is now more easily accessible thanks to the Flask connection. Users can interact with the custom CNN and view the enhanced results in real-time with ease. By using a pyramid-based fusion technique, the suggested method produces traffic photographs of the highest caliber. This last stage makes sure that the improved photos have more realistic colors and details than possible with the approaches that are currently in use. Extensive studies on a wide range of pictures demonstrate that our system regularly outperforms existing methods, suggesting that it is a viable alternative for improving roadside images at night in intelligent transportation systems.

Pyramid-Based Fusion

1. **Decomposition:** The input image is decomposed into multiple scales using Gaussian pyramids.
2. **CNN Feature Extraction:** Each level is processed by the CNN to extract features.
3. **Fusion:** Enhanced features from different levels are fused using weighted averaging

$$F_{\text{enhanced}} = \sum_{i=1}^{N} w_i \times F_{\text{CNN}}(L_i)$$

where w_i is the weight at level i and $F_{\text{CNN}}(L_i)$ is the CNN output.

V. RESULTS AND DISCUSSION

Our method is compared with:

- Histogram Equalization (HE)
- Retinex-based algorithms
- Deep learning models: LL Net, Enlighten GAN

Table 1: Compararios of models.

Method	PSNR (dB)	SSIM	Time (s)
Histogram Eq.	15.8	0.45	0.01
Retinex	18.4	0.65	0.12
EnlightenGAN	21.9	0.82	0.52
Proposed	**25.3**	**0.88**	**0.47**

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Table 2: Comparative Results of Low-Light Image Enhancement Methods.

Method	PSNR (dB)	SSIM	Perceptual Quality (LPIPS)	Inference Time (s)
Histogram Equalization (HE)	15.8	0.45	0.72	0.01
Gamma Correction	17.3	0.53	0.65	0.02
Retinex Algorithm	18.4	0.65	0.58	0.12
LLNet (Deep CNN)	20.7	0.75	0.51	0.30
EnlightenGAN	21.9	0.82	0.43	0.52
Zero-DCE	22.6	0.83	0.40	0.35
Proposed Method	**25.3**	**0.88**	**0.33**	**0.47**

VI. CONCLUSION

To facilitate multi-object detection and recognition tasks on the Intelligent Roadside Surveillance System, we propose an efficient flowchart for night image enhancement by employing multisource data fusion. Using a fixed field of view and easy multi-sensor fusion, we present a complete set of multi-sensor fusion schemes suitable for the intelligent roadside system. The two key fusions are the decision-level fusion of camera and radar and the pixel-level fusion of day and night images.

In the future, this project could be expanded and enhanced in several ways to further improve nighttime roadside image quality for intelligent transportation systems. One avenue of development could involve refining and optimizing the proposed bidirectional area segmentation-based inverse tone mapping technique to achieve even better results in preserving natural color representation while enhancing image quality. Additionally, further research could focus on enhancing the highlighting method for moving objects, potentially incorporating advanced motion tracking algorithms or machine learning techniques for more accurate identification and highlighting. Another area for future enhancement could involve exploring new sensor technologies or data fusion techniques to improve the effectiveness of the pyramid based fusion approach, enabling even higher-quality image generation. Furthermore, ongoing experimentation and validation with larger and more diverse datasets could provide valuable insights into the robustness and generalizability of the proposed method, paving the way for its potential integration into real-world intelligent transportation systems. Overall, future enhancements could continue to push the boundaries of nighttime image enhancement, ultimately leading to safer and more efficient transportation systems.

VII. 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 visionrelated roadside surveillance system using compound hierarchical-deep models,” IET Intelligent Transport Systems, vol. 14, no. 11, pp. 1353–1362, 2020.

[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 color 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 International Conference on Electronic Communications, Internet of Things and Big Data (ICEIB), 2021, pp. 196–198. [12] 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.

[12] F. Xu, J. Liu, Y. Song, H. Sun, and X. Wang, "Multi-exposure image fusion techniques: A comprehensive review," Remote Sensing, vol. 14, 2022.

[13] X. H. Xu K, Wang Q and L. K, "Multi-exposure image fusion algorithm based on improved weight function," Neurorobot, 2022.