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MULTI-SCALE AGGREGATION RESIDUAL CHANNEL ATTENTION FUSION NETWORK FOR SINGLE IMAGE DERAINING

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ABSTRACT
Adverse weather conditions such as rain significantly degrade the quality of outdoor images, impairing visual perception and compromising the effectiveness of computer vision systems. This project introduces the Multiscale Aggregation Residual Channel Attention Fusion Network (MARC-AFNet) as an innovative approach to mitigate the adverse effects of rain on outdoor image quality, particularly in the context of computer vision systems. MARC-AFNet integrates three core mechanisms: multiscale aggregation, residual learning, and channel attention, to effectively remove rain streaks while preserving essential image details. The multiscale aggregation module facilitates comprehensive deraining by capturing rain streaks at varying scales, enhancing the network's overall performance. Furthermore, the residual learning scheme improves deraining accuracy by enabling the network to better learn residual rain features. Additionally, the channel attention mechanism selectively emphasizes pertinent rain-related features while suppressing irrelevant ones, allowing MARC-AFNet to focus its efforts on rain-related structures for more efficient deraining. Extensive experimentation on benchmark datasets demonstrates MARC-AFNet's superiority over state-of-the-art methods in terms of both quantitative metrics an d visual quality. This proposed methodology holds significant promise for real-world applications, particularly in domains such as autonomous driving, surveillance, and outdoor scene analysis, where precise image deraining is paramount for informed decision-making and perception.

Keywords: MARCAFNet, multi-scale aggregation, residual channel attention fusion network, deraining.

INTRODUCTION

Unfavorable weather, like rain, frequently degrades the quality of photographs taken outside, which affects important computer vision activities like object detection and intelligent vehicle operation. In order to overcome these obstacles, algorithms that can restore distorted images and eliminate artifacts even in the face of unknown background information must be developed. Over the past few decades, a number of research have addressed these problems and offered a wide range of solutions for rain removal. Among them are methods that use wave filters, such as guided and bilateral filters, to split up rainfall images into high- and low-frequency segments for eventual reconstruction. Lately, theoretical investigations of background layers and rain have given rise to new approaches that use methods such synthesis sparse coding, joint convolutional analysis (JCAS), discriminative sparse coding (DSC), and Gaussian mixture models (GMM). Nevertheless, photos with intricate backdrops and patterns of rain pose challenges for these analytical models. Researchers are looking into novel approaches for rain removal as a result of the development of deep learning in computer vision. Robust performance is achieved via deep learning techniques like RESCAN, PReNet, LPNet, MSPFN, MPRNet, VRGNet, PCNet, and RAiANet,

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which rely on complex structures, copious amounts of training data, and nonlinear representation modeling. Deep learning models have benefits, but their depth presents problems like vanishing and ballooning gradients. Furthermore, existing approaches frequently focus too little on structural representation in their loss functions and overlook multi-scale feature encoding, which results in subpar performance. In order to overcome these drawbacks, a unique deep learning architecture specifically designed for picture deraining is proposed in this dissertation.

LITERATURE SURVEY

Fu, Kang, and Lin initially employed bilateral filters in their early rain removal methods, employing image processing and machine learning techniques to distinguish between high and low frequencies. Subsequently, they employed sparse coding dictionaries to isolate and reconstruct rain-affected areas from the high-frequency components.

Li et al. pioneered a hybrid model integrating Gaussian Mixture Models (GMMs) gleaned from natural photos, enabling comprehensive rain streak removal from both

backgrounds and rain layers. Meanwhile, Wang et al. utilized guided filters to partition images into high and low frequencies, facilitating effective rain removal by recovering image features from the high-frequency components.

Zhu et al. innovated by decomposing single images into rain-free backgrounds and rain streak layers, leveraging local gradient information for removal. This method not only effectively removed rain streaks but also optimized memory usage. However, as technology advances, concerns about image resolution persist, urging further enhancements.

Jiang et al. introduced a progressive coupled network (PCNet) focused on preserving rain-free details while effectively separating rain streaks, leveraging blending correlations and a coupled representation module (CRM).

Yin and Deng proposed RAiA-Net, a multi-stage network enhanced with a refined attention mechanism for image deraining. Despite previous advancements, challenges like blurring and loss of texture details persist, prompting the development of a novel multi-scale aggregation residual channel attention fusion network for robust single image deraining.

EXISTING SYSTEM

This innovative methodology introduces the Bilateral Recurrent Network (BRN), which integrates the strengths of the Single Recurrent Network (SRN) and Bilateral Long Short-Term Memory Networks (BLSTMs). At its core, the SRN orchestrates the extraction of rain streaks and prediction of pristine background images across multiple stages, employing direct and residual mapping strategies. It comprises an intricate architecture, encompassing input layers for image assimilation, recurrent layers for progressive rain streak removal, residual blocks for feature extraction, and output layers for generating derained images.

The subsequent evolution, BRN, pioneers the fusion of two SRNs, orchestrating simultaneous rain streak extraction and background image prediction. BLSTMs play a pivotal role, fostering dynamic interaction between these layers and augmenting the deraining process. Notably, the training regimen for the enhanced BRN model is

streamlined, consolidated under a single loss function, such as negative Structural Similarity Index (SSIM) loss, thus simplifying the learning paradigm.

Empirical validation underscores the potency of this approach, with the negative SSIM loss serving as a robust training metric for both SRN and BRN. This unified framework yields tangible enhancements in deraining performance, substantiated through comprehensive qualitative and quantitative assessments.

DISADVANTAGES

- Vanishing and Exploding Gradient Problem: In bilateral recurrent networks for single image deraining, the issue of vanishing or exploding gradients during training can hinder the convergence of the model, making it challenging to effectively learn the complex relationships between rain streaks and background details over multiple recurrent stages.
- Complexity in Handling Multi-Scale Rain Patterns: Bilateral recurrent networks may struggle to efficiently handle multi-scale rain patterns present in images, as capturing and effectively modelling variations in rain streak sizes, densities, and shapes across different spatial scales requires intricate network architectures and training strategies.
- Receptive Field Size: Ensuring an adequate receptive field size in bilateral recurrent networks is crucial for capturing contextual information across different regions of the image. However, balancing the receptive field size to capture both local and global features effectively while avoiding computational and memory constraints poses a significant challenge in the deraining process.

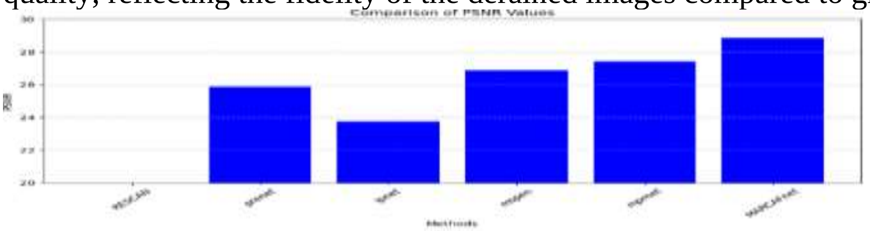
PROPOSED SCHEME

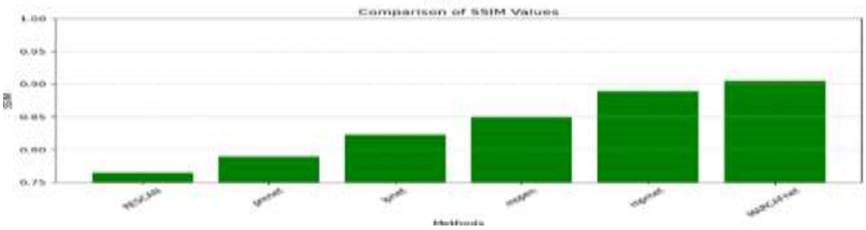
The Multi-Scale Aggregation Residual Channel Attention Fusion Network (MARCAFNet) introduces a sophisticated architecture designed to proficiently remove rain streaks from images. Its framework integrates convolutional layers alongside three coding structure (CS) blocks, each equipped with distinct dilation sizes to capture features at multiple scales. The dense interconnection within CS blocks promotes efficient feature sharing, mitigating the risk of gradient vanishing. To enhance channel features, the model incorporates a residual channel attention (RCA) block, while a cross-stage feature fusion (CSFF) block facilitates seamless

integration of features across CS blocks. A pivotal component, the scale blend (SB) block, aggregates features from each CS block, fostering comprehensive feature representation. Training is orchestrated through a balanced loss function, comprising structural similarity (SSIM) loss and mean square error (MSE) loss, ensuring holistic model optimization. This intricate architecture empowers MARCAFNet to adeptly capture and recover rain-related details across diverse scales, culminating in the production of high-quality, derained images.

Graphs of Different Datasets with PSNR and SSIM Values:

Graphs depicting the PSNR and SSIM values across different datasets provide valuable insights into the performance of MARCAFNet. The PSNR and SSIM values serve as objective measures of image quality, reflecting the fidelity of the derained images compared to ground truth images.





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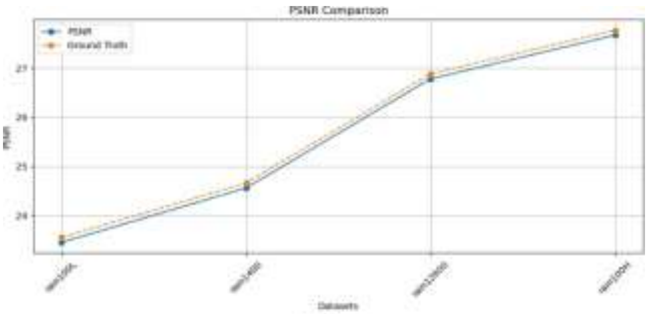
ADVANTAGES

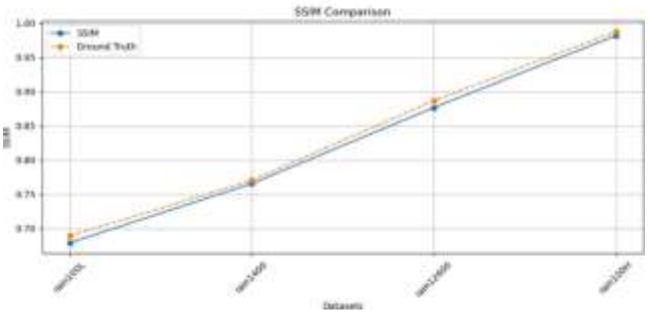
- Multi-Scale Feature Extraction: MARCAFNet employs coding structure (CS) blocks with varying dilation sizes to capture features at multiple scales. This allows the model to effectively extract both micro-features and structural features, as well as features related to larger areas such as rain streaks. By incorporating dilated convolutions with different rates, MARCAFNet can adaptively adjust the receptive field size, enhancing its ability to capture diverse information in the input image.
- Feature Fusion and Sharing: The architecture includes mechanisms such as densely connected convolutional layers, residual channel attention (RCA) blocks,

and cross-stage feature fusion (CSFF) blocks, which facilitate feature fusion and sharing across different stages of the network. This enables the model to leverage information from previous stages, enhancing the learning process and improving the overall performance of the deraining task.

- Enhanced Channel Attention: The integration of residual channel attention (RCA) blocks enhances channel-wise attention within the network. By combining the features of SE (Squeezeand-Excitation) modules with those of Res Net modules, the RCA blocks effectively address the issue of gradient vanishing and enhance feature representation. This attention mechanism enables MARCAFNet to focus on important features while suppressing irrelevant information, leading to more accurate deraining results.

COMPARISION OF PARAMETERS WITH GROUND TRUTH





SYSTEM BLOCK DIAGRAM

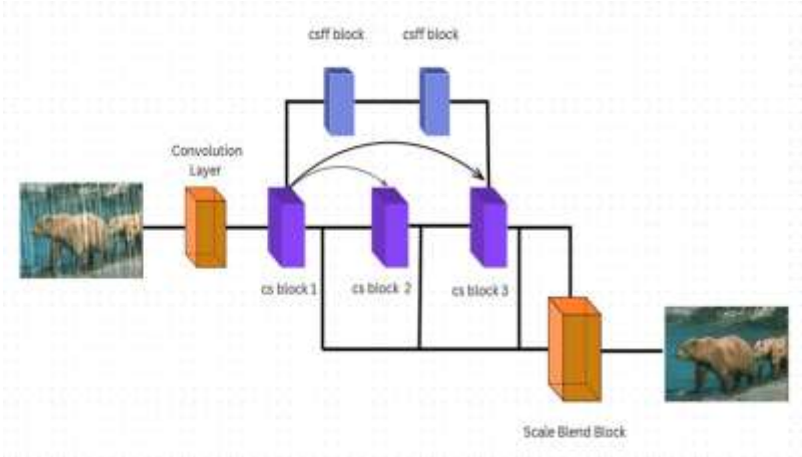


Fig1: System Architecture

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OUTPUT SCREENS

Fig 2: Output Page

CONCLUSION

The MARCAFNet architecture introduces a novel approach to image deraining by leveraging kernels with different dilation rates to effectively recover image features and remove rain streaks. By integrating the RCA block into the CS block, inspired by the U-Net architecture, the model enhances image content representation, enabling detailed feature extraction from rain-streaked images. Additionally, the CSFF block facilitates the transfer of channel features between encoder-decoder pairs of the same scale, enhancing image detail information by incorporating larger receptive fields. Through the consecutive connection of three CS blocks, the model captures textural, contour, and rain streak features, which are then aggregated by the SB block into a new feature map. Finally, adaptive summation yields the recovered image. MARCAFNet demonstrates superior performance over existing methods, emphasizing the importance of integrating global and local loss functions to preserve both image structure and local features during single image deraining.

REFERENCES

1. Sun Miller, R. (2002). "Detection of vehicles on roads utilizing Gabor filters and support vector machines." Proceedings of the International Conference on Digital Signal Processing, held in Santorini, Greece.
2. Janai, J., Guney, F., Behl, A., & Geiger, A. (2020). "Exploring Computer Vision Applications in Autonomous Driving: Challenges, Data Resources, and Recent Advances." A comprehensive review published in Foundations and Trends in Computer Graphics and Vision.
3. Wang, Y., Liu, S., Chen, C., & Zeng, B. (2017). "A hierarchical method for removing rain or snow artifacts from individual color images." Published in the IEEE Transactions on Image Processing.
4. Ren, D., Zuo, W., Hu, Q., Zhu, P., & Meng, D. (2019). "Advancing image deraining techniques: Progressive networks for enhanced performance."IEEE Conference , Long Beach, CA, USA.
5. Fu, X., Liang, B., Huang, Y., Ding, X., & Paisley, J. (2020). "Lightweight pyramid networks designed for efficient image deraining." Published in the IEEE Transactions on Neural Networks and Learning Systems.
6. Jiang, K., Wang, Z., Yi, P., Chen, C., Huang, B., Luo, Y., Ma, J., & Jiang, J. (2020). "Multi-Scale Progressive Fusion Network: A novel approach for single image deraining." IEEE Conference , Seattle, WA, USA.

http://doi.org/10.36893/JNAO.2024.V15I1N01.264-268