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SH-RNet: Dual-branch Network for Joint Specular Highlight and Reflection Removal

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Abstract

Removing reflections from an image is a very important task in image processing. Many times, we capture photographs of objects inside a glass. In such a case, the image has glass reflections. Sometimes these reflections are intense. There are many state-of-the-art methods for reflection removal. Although they produce good results, they cannot remove intense reflections. This paper focuses on removing intense reflections from an image. Most of the state-of-the-art methods focus on glass reflections. Specular highlights, another important component, commonly occur as a part of reflections. Specular highlights are strong and shiny dots. Reflections and specular highlights are image degradation artifacts that adversely affect visual quality and reduce the performance of computer vision applications. A Specular Highlights and Reflection Removal Network algorithm has been proposed. The algorithm removes both glass reflections and specular highlights. The Single Image Reflection Removal Dataset, a benchmark dataset, is used to conduct a range of experiments. The proposed model also shows a significant improvement over state-of-the-art technique. A lightweight deep learning model is used that works better when images have intense reflections. The results indicate that the proposed framework effectively suppresses reflections and specular highlights while preserving image details, making it suitable for applications in image enhancement, object recognition and computer vision systems.

Keywords: Deep Learning, Image Processing, Single Image Reflection Removal, Specular Highlights.

Introduction

Reflection and specular highlight removal are important in computer vision and image processing as they significantly affect the quality of captured images through a camera. Images captured from the camera have noise. In image processing, glass reflections refer to the unwanted overlay that appears when you capture a scene through a transparent surface. Specular highlights are the bright, shiny spots that appear on an object when light reflects directly towards the viewer from a smooth or glossy surface. Such reflections are difficult to process. The Single Image Reflection Removal Dataset (SIR2), a benchmark dataset, shows such reflections (1). Specular highlights can distort colour, texture and shape information, leading to errors in feature extraction and model predictions. In applications like autonomous driving, medical imaging, surveillance, museum imaging and augmented reality, properly managing these reflections improves image quality and visual clarity. So, there is a need to make a unified model that will remove both glass reflections and specular highlights. The current state-of-the-art focuses only on glass reflections. They can't remove specular highlights. The Specular Highlights and Reflection Removal Network (SH-RNet) has been proposed, which is a single-image reflection removal network that explicitly incorporates a Dichromatic Reflection Model (DRM) branch for joint reflection removal and specular highlight removal. So, when images have both glass reflections and specular highlights, this method will overcome both. Figure 1A shows an image with a reflection, Figure 1B shows a clean image and Figure 1C demonstrates reflection. Many researchers have worked on removing reflections from an image. However, removing specular highlights is a relatively less addressed topic. There are different approaches for reflection removal, such as the traditional approach and the deep learning-based approach (2, 3).

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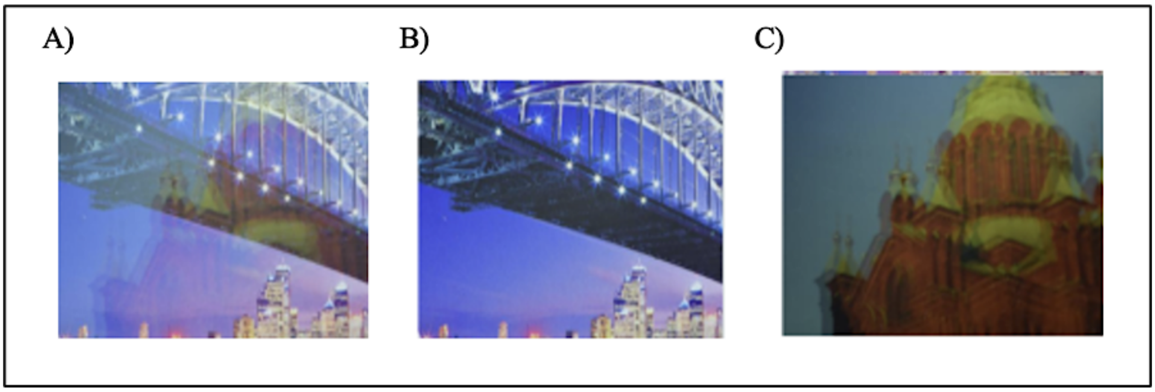

Figure 1: Image Having Reflection. (A) Input Image, (B) Transmitted (Clean Image), (C) Reflection (1)

Traditional Approach for Reflection Removal

This approach uses handcrafted features for removing reflections. Normally, reflections are blurred, ghosted and have low frequencies. The researcher used various techniques based on sparse gradients, ghosting cues, etc., for removing reflections (4, 5). The researcher used gradient thresholding and convex optimization for removing reflections (6). The researcher used the discrete cosine transform for removing reflections (7). Traditional approaches are unable to remove specular reflections effectively. These approaches are not robust for real-world applications.

Deep Learning-based Approach for Reflection Removal

Deep learning-based approaches learn patterns of reflections from the training dataset and try to remove reflections from the images in the test dataset to output clean images. There are deep learning approaches based on Convolutional Neural Network (CNN), Generative Adversarial Networks (GAN) and transformers. CNN-based models are fast and stable, so many researchers are using them (8-13).

Enhanced Reflection Removal Network (ERRNet) learns edge-aware representations and contextual features (8). ERRNet removes blurred reflection and preserves sharp edges, but it ignores specular reflections. Reflection-Aware Guidance (RAGNet) is a two-stage network that improves reflection removal by explicitly identifying where reflections exist and guiding the network to focus on those regions (9). This model focuses only on reflection-heavy regions. This model gives better accuracy than ERRNet, but it cannot remove complex reflections and specular highlights. Dual-stream Semantic-aware network with Residual correction (DSRNet) is a deep stacked refining network that progressively refines the image through multiple stages (10). Although this network can handle specular reflections, its heavy model makes it unsuitable for real-time applications. Reversible Decoupling Network (RDNet) introduces a reversible encoder to preserve critical information while effectively separating transmission and reflection features, overcoming limitations of feature loss and rigid dual-stream interactions (11). RDNet has a more complex architecture and its training is harder.

All the mentioned reflection removal algorithms focus only on glass reflections.

Specular Highlights Removal

The most widely adopted theoretical basis for specular highlight removal is the DRM proposed in a study (14).

It models the reflected light as:

$$I(x) = D(x) + S(x) \qquad [1]$$

Here, in Equation [1], I(x) is an observed image which is a combination of diffused reflection D(x) and specular reflections S(x).

Diffused reflection is when the light scatters in many directions and the object gets its base colour. Specular reflection, which is also called a specular highlight, is when the light reflects in a single, mirror-like direction. It appears as a bright white or intense spot.

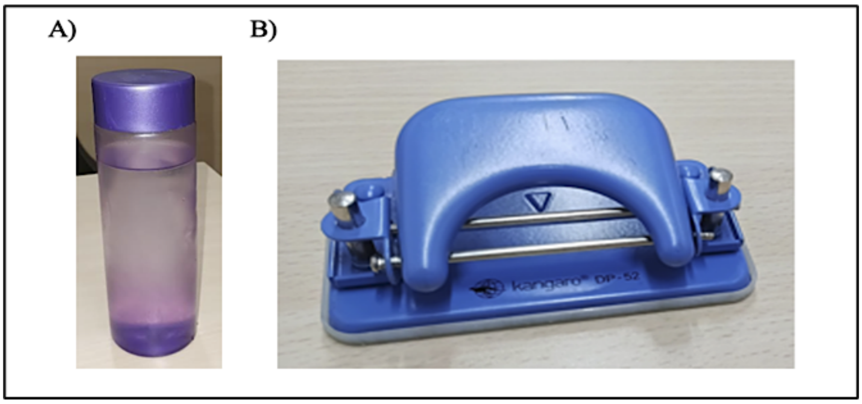

Figure 2: Images with Specular Highlights. (A) Specular Highlight Image 1, (B) Specular Highlight Image 2

Images with specular highlights are shown in Figure 2. We can see shiny surfaces, bright ones, in both images, as shown in Figures 2A and 2B. These are called specular highlights.

The researcher proposed neural DRM for specular highlight removal (15). The researcher proposed a novel and effective method based on DRM and total variation (TV) optimization to remove specular highlights (16). The researcher used DRM and exemplar patch matching for specular highlight removal (17). The researcher discussed various traditional and deep learning techniques for removing specularity (18).

As of now, no method can deal with reflections and specular highlights removal simultaneously. A unified model has been proposed in this paper that will address both issues concurrently.

Combine specular highlights and glass reflection. The new formula should be as in Equation [2]:

$$I(x) = T(x) + R(x) + S(x) \qquad [2]$$

Where I(x) - observed image, T(x) - transmission, R(x) - glass reflection, S(x) - specular highlight.

The following are the objectives of the research work:

a) To get a clean image by removing reflections from the raw image
b) To get a clean image by removing specular highlights

Methodology

The study proposes SH-RNet, which removes reflections and specular highlights from raw images.

SH-RNet Architecture

As shown in Figure 3, the encoder-decoder part performs reflection removal, while the DRM branch removes specular highlights. The researchers used an encoder-decoder architecture in which the encoder extracts feature progressively (19-25). The Encoder1 detects pixel-level reflection clues like blurriness, colour shifts and soft edges at every pixel. The Encoder2 detects regional reflection patterns. The Bottleneck makes a global scene-level judgment of real content versus reflection by seeing large image portions. The Decoder2 removes reflections at the region level, which keeps real content and in paints the hidden background at reflection regions. The Decoder1 restores pixel-level sharpness from e1 only at real content positions. The DRM branch predicts the specular highlight map and location mask in parallel. Finally, there is a fusion of the reflection-free image and the specular highlights-removed image, which will be the final output.

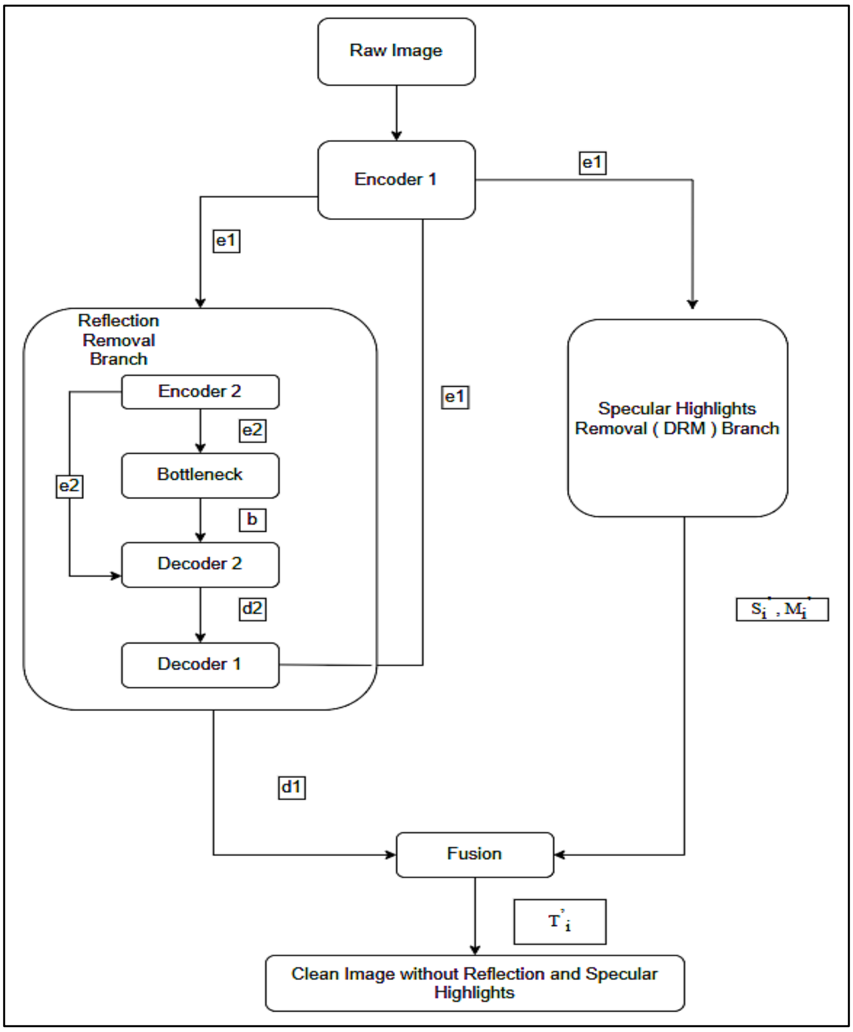

Figure 3: SH-RNet Model Architecture

Assume N as the total no of images, C for no of channels, H for the height and W for the width of an image. Equation [3] can be written in terms of a mathematical equation as:

$$\text{Clean image} = \sum_{i=0}^{N} \sum_{j=0}^{C} \sum_{k=0}^{H} \sum_{l=0}^{W} \text{Ref\_free}_{(i)}\,[\,j, k, l\,] \;||\; \text{Spec\_free}_{(i)}\,[\,j, k, l\,] \qquad [3]$$

Where Ref_free is the reflection-free image obtained from the encoder-decoder branch, Spec_free is the specular highlights-free image.

Algorithm

The SH-RNet forward pass algorithm takes a set of images from the SIR2 dataset as input and generates a set of clean images that are free from reflections and specular highlights. This algorithm uses an encoder-decoder architecture for reflection removal and DRM for specular highlights. Reflection removal and specular highlights: both branches work in parallel and at the end, there is a fusion of the reflection-free image and the specular highlights-removed image.

ALGORITHM: SH-RNet Forward Pass

INPUT: Set of raw images $D = \{I_n\}_{n=1}^{N}$ where N = total number of images and $I_n \in [0,1]^{C*H*W}$ where C = no. of channels, H = height of the image and W = width of the image

OUTPUT: A set of clean images $\{T_n'\}_{n=1}^{N}$ where $T_n' \in [0,1]^{C*H*W}$

```
For i←0 to N do
        For j ←0 to C do
                For k← 0 to H do
                        For l← 0 to W do
```

a. Extract pixel $p = I_i[j, k, l] \in [0,1]$
b. Pass p through Encoder 1 to obtain feature e1[j, k, l]
c. Check for specular highlights (Path A)
$S_i'[j, k, l], M_i'[j, k, l] = DRM(e1[j, k, l])$
Where $S_i'[j, k, l]$ and $M_i'[j, k, l]$ are the specular map and specular mask, respectively.
$I\_despec_i = I_i - S_i' \odot M_i'$ where $\odot$ is an element-wise multiplication, also called the Hadamard Product
d. Check for reflections (Path B)
Pass e1[j, k, l] to Encoder2 to Bottleneck and Decoders to get $d_{1(i)}[j, k, l] = Dec_1([U_{\times2}(d_{2(i)}) \| e_{1(i)}])[j, k, l]$

Where $d_{1(i)}[j, k, l]$ is a pixel-level reflection-removed feature, $d_{2(i)}$ is the region-level reflection-removed feature map, $e_{1(i)}$ is the regional feature map at half resolution, detecting ghost edges and spatial inconsistencies, $U_{\times2}$ is bilinear up sampling by factor 2.
e. Fusion (Join path A and B)
$T'_i[j, k, l] = d_{1(i)}[j, k, l] \,||\, I\_despec_i[j, k, l]$

End For l

End For k

End For j

End For i

Return $\{T'_n\}$

Results and Discussion

Dataset Description

The SIR2 dataset has been used in this work. SIR2 is a widely used benchmark dataset for evaluating single-image reflection removal algorithms. It has 3 sub-datasets as shown in Table 1, namely the Postcard dataset, the Solid Object dataset and the Wild Scene dataset. It has blended, transmitted and reflected layer images. SH-RNet was trained using SIR2 for 100 epochs. The image size was 128 and the batch size was 16.

Table 1: SIR2 Dataset Distribution Across Image Pairs

Dataset	Solid Object Dataset	Wild Scene Dataset	Postcard Dataset	Total pairs
Pairs	200	101	198	499

Performance Measures

Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) were calculated. PSNR is a common metric used in image and video processing to measure the quality of a reconstructed or compressed signal compared to the original. SSIM is a metric used to evaluate how similar two images are, especially in terms of how humans perceive image quality.

Table 2 shows an overall comparison of PSNR on the SIR2 dataset with state-of-the-art methods. The proposed algorithm has been compared with ERRNet, RAGNet, RDNet and DSRNet. As shown in Table 2, for the Solid Object Dataset and Post Card Dataset, SH-RNet gives the highest PSNR as compared to ERRNet, RAGNet, DSRNet and RDNet. This is due to adding a second component for specular highlight removal in SH-RNet. Also, the average PSNR of SH-RNet is higher than ERRNet, RAGNet, DSRNet and RDNet.

Table 2: Overall Comparison of PSNR on the SIR2 Dataset with State-of-the-art Methods

State-of-the-Art Methods	PSNR for Solid Object Dataset in dB	PSNR for Wild Scene Dataset in dB	PSNR for Postcard Dataset in dB	Average PSNR for SIR2 Dataset	References
ERRNet	24.87	22.04	24.25	23.72	(3)
RAGNet	26.15	23.67	25.53	25.12	(4)
DSRNet	26.81	24.72	27.02	26.18	(5)
RDNet	26.78	26.33	27.70	26.94	(6)
SH-RNet (Proposed)	29.91	23.44	28.87	27.41	-

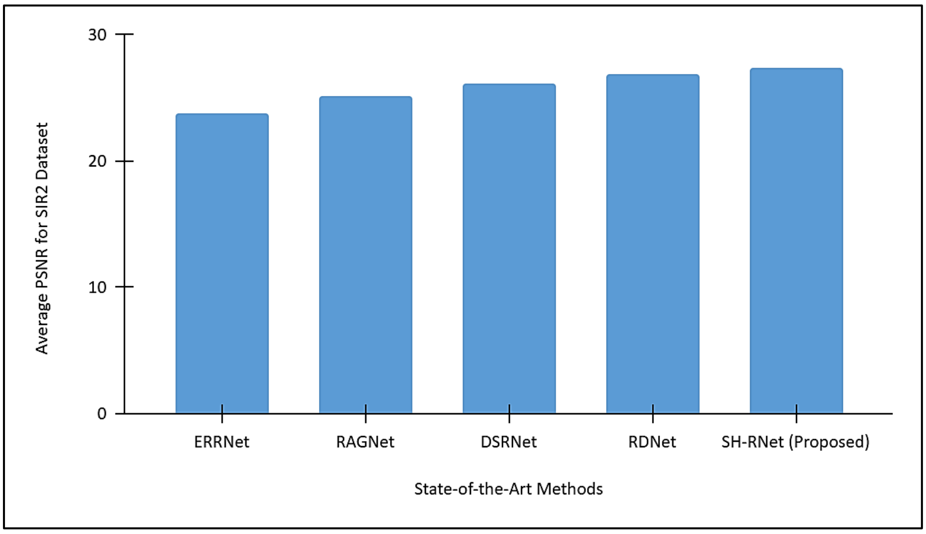

Figure 4: Comparison of the Average PSNR of SH-RNet with Others on the SIR2 Dataset

Figure 4 shows a comparison of the average PSNR of SH-RNet with others on the SIR2 dataset. We can conclude that the average PSNR of the SH-RNet model is better than that of ERRNet, RAGNet, DSRNet and RDNet.

Results obtained after applying SH-RNet on the SIR2 dataset are shown in Figures 5A-5R. Since the SIR2 dataset does not provide explicit specular reflection labels, pseudo ground-truth masks are generated by computing the brightness difference between the blended image and the transmission image. Any pixel brighter than the background is considered a specular highlight. Specular highlights are subtracted from the raw image. For non-specular regions, no information is subtracted. In specular regions, the predicted highlight colour is fully removed before the image is passed to the decoder. This enables the network to suppress specular reflections while preserving normal image content selectively.

Better PSNR and SSIM values can be attributed to the adaptive feature extraction method. The proposed method effectively removes the reflection layer and specular highlights from the raw image. Higher SSIM values indicate that the proposed method helps in preserving structural information. Better PSNR demonstrates improved reconstruction quality. Overall, it can be said that reflection noise and specular highlights are effectively removed from the raw images.

As shown in Figure 5, sample images from the SIR2 dataset have been processed. We can get a clean image when we apply SH-RNet to raw images from the SIR2 dataset. Figures 5B, 5H and 5N are the clean images from the SIR2 dataset, while Figures 5C, 5I and 5O are the clean images obtained from the SH-RNet algorithm.

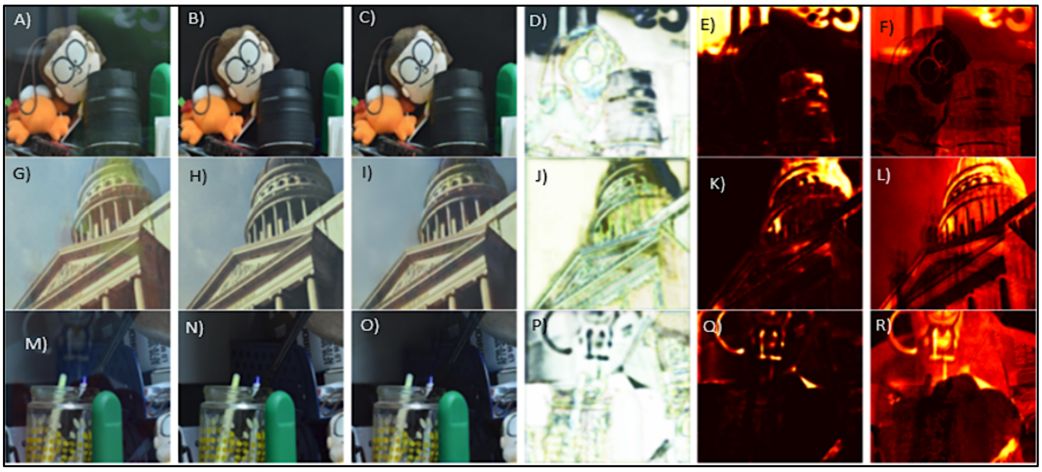

Figure 5: Sample Results from the SIR2 Dataset Using SH-RNet. (A, G, M) Raw Images, (B, H, N) Clean Image from SIR2, (C, I, O) Clean Image Obtained From SH-RNet, (D, J, P) Specular Map, (E, K, Q) Specular Mask, (F, L, R) Specular Bright Difference

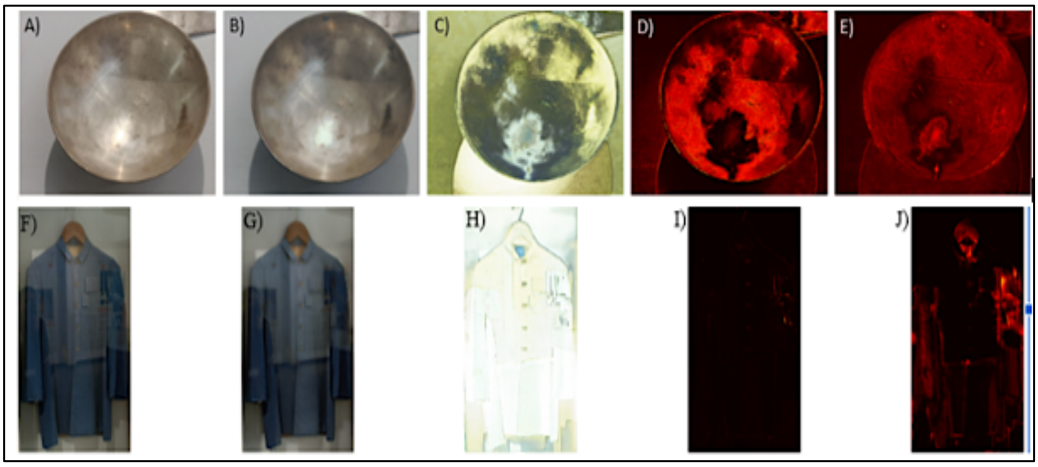

Figure 6: Sample Results of the Museum Objects Dataset Using SH-RBNet. (A, F) Museum Object 1 And Object 2, (B, G) Output From SH-RNet, (C, H) Specular Map, (D, I) Specular Mask, (E, J) Removed Component

The proposed algorithm has been applied to real-time museum objects to get a clean image. Results are shown in Figures 6A- 6J below. We can see the raw image in Figure 6A; Figure 6F has reflection and specular highlights and Figures 6B and 6G are clean images obtained from SH-RNet.

Conclusion

In this work, SH-RNet, a lightweight dual-branch convolutional neural network designed for the joint removal of reflections and specular highlights from a single image. This problem that has been largely overlooked in the existing literature. Unlike prior reflection removal methods that treat the captured image as a simple superposition of a transmission layer and a reflection layer, SH-RNet explicitly accounts for the additional degradation introduced by specular highlights, which commonly arise in real-world photography involving glass surfaces, wet environments and glossy objects. This joint modelling represents a meaningful departure from conventional formula-tions and addresses a critical gap in single-image restoration research.

The proposed architecture adopts an encoder-decoder backbone that progressively captures multi-scale contextual features while preserving fine spatial details essential for accurate layer separation. Complementing this, the DRM branch operates in parallel to explicitly decompose and suppress specular highlight artifacts by leveraging the dichromatic reflection model, which separates the observed image into diffuse and specular components. The dual-branch design consequently allows the reflection removal and specular suppression sub-tasks to mutually reinforce each other, leading to cleaner and more visually faithful transmission estimates. Extensive experiments conducted on the SIR2 benchmark, a widely adopted evaluation suite comprising three challenging subsets, demonstrate that SH-RNet achieves state-of-the-art performance across all subsets, outperforming existing single-image reflection removal methods in both quantitative metrics and perceptual visual quality. These results validate the effectiveness of grounding specular highlight removal within the dichromatic reflection framework as an integral component of the reflection removal pipeline and confirm that the dual-branch design successfully captures the complementary nature of the two degradation types.

Limitations

Despite these promising results, the current work has certain limitations that merit acknowledgment. SH-RNet is designed to jointly address glass reflections and specular highlights; however, real-world images frequently contain other co-occurring degradations such as shadows, which are not accounted for in the present formulation. When shadow artifacts appear alongside reflections and specular highlights, they may adversely affect the quality of the restored output. Addressing such compound degradations within a unified framework remains an open challenge for future work. Furthermore, the current method operates exclusively on single static images and does not exploit temporal information, limiting its direct applicability to video sequences where reflections and highlights may vary dynamically across frames.

Future Scope

The promising results achieved by SH-RNet open several meaningful avenues for future research and real-world application. One particularly compelling application domain is cultural heritage preservation, specifically in museum environments where valuable artifacts are displayed within glass cases under varied and complex lighting conditions. Such settings inherently produce both glass reflections and specular highlights simultaneously, severely degrading image quality. Applying SH-RNet as a preprocessing stage in this context can yield clean, reflection-free images of historical objects, which is especially valuable for digitization initiatives and three-dimensional model generation, where high-fidelity input images are a prerequisite for accurate and visually coherent 3D reconstructions. Beyond cultural heritage, SH-RNet holds strong potential in the domain of autonomous driving, where reflections from windshields, wet road surfaces and shiny vehicle exteriors can significantly impair the performance of downstream perception modules. Removing such noise can directly improve the reliability of road sign detection, pedestrian recognition and obstacle avoidance systems, thereby contributing to safer and more robust autonomous navigation. Similarly, in Augmented Reality (AR) and Virtual Reality (VR) systems, unwanted reflections and specular highlights reduce scene realism and degrade spatial tracking accuracy. Integrating a lightweight reflection and highlight removal module such as SH-RNet into AR/VR pipelines can meaningfully enhance visual immersion and system responsiveness.

Abbreviations

AR: Augmented Reality, CNN: Convolutional Neural Network, SH-RNet: Specular highlight and reflection removal network, SIR2: Single Image Reflection Removal Dataset, VR: Virtual Reality.

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Author Contributions

Simantinee Vinit Kulkarni: Conceptualization, Methodology, Validation, Software, Formal Analysis, Investigation, Resources, Data Curation, Writing – Original Draft Preparation, Anagha Ravindra Kulkarni: Writing - Review, Editing, Conceptualization, Formal Analysis, Radhika Akshay Bhagwat: Visualization, Conceptualization, Formal Analysis, Supervision. Authors have read and agreed to the published version of the manuscript.

Conflict of Interest

The authors declare no conflict of interest.

Data Availability

The datasets used in this study were obtained from the public domain; however, the compiled data can be made available from the corresponding author upon a reasonable request.

Declaration of Artificial Intelligence (AI) Assistance

The authors declare that no generative AI or AI-assisted technologies were used in the conception, drafting, editing, data analysis, figure preparation, or referencing of this manuscript. All content was created solely by the authors.

Ethics Approval

Not applicable.

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