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PDE-based Specular Highlight Elimination

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ABSTRACT

Dealing with reflections in images captured through glass would be real headache, as they can obscure the important stuff behind the glass and make the whole image look messy. This is a major problem in many computer vision tasks.Early studies reported that a popular way to tackle the challenge of removing reflections from [1] single images in deep learning. In this article, we take a deep dive into the research on this topic from 2015 to 2021, focusing on how deep learning is being used for [5] single-image reflection removal [4].We searched through a bunch of important online databases and libraries, like IEEE Xplore, Google Scholar, ScienceDirect, SpringerLink, and ACM Digital Library, to find relevant research papers. After carefully going through them, we picked out 25 papers [9] that fit the criteria for our review.We analyzed these papers to answer seven major questions about how deep learning and [3] neural networks are being used for [6] single-image reflection removal. This will hopefully give future researchers a good understanding of what's been done in this area and help them build on that knowledge.The review also highlights the important challenges that data scientists are facing in this area, and also some promising directions for future research. . And importantly, it provides a list of useful datasets that data scientists can use to benchmark their own deep learning techniques against other studies. Whether you're a researcher hungry for the next challenge or just someone who wants to understand how it all works, this review will equip you with the knowledge and inspiration to delve deeper into this fascinating field.

Key words: Anisotropic diffusion, boundary constraints, diffusion coefficients, image inpainting, non-local methods, partial differential equations (PDEs), specular highlight modeling, texture preservation ,Variational Framework

1. INTRODUCTION

Isolating reflections in images is tricky, especially for diverse materials like plastics, leaves, wood, and skin. This separation matters because the final image is a blend of specular (mirror-like) and diffuse (rough) reflections, weighted by the material's inherent reflectivity. Breaking down an image into these parts unlocks several benefits.

The Lambertian model perfectly captures diffuse reflection, making it a powerful tool for real-world 3D scene analysis and object recognition, even when surfaces aren't perfectly Lambertian.

Specular reflections, besides influencing our perception, are crucial for certain computer vision algorithms. Furthermore, separating specular and diffuse components is vital in 3D modeling and photo editing, allowing independent manipulation and recombination of these layers. This paper tackles the challenge of separating reflection components in diverse images, potentially including textured surfaces. It focuses on surfaces accurately described by Shafer's dichromatic reflectance model, where specular reflections match the light source's color, and diffuse reflections depend on the material's properties[10] . The goal is to split an RGB image into an RGB "diffuse image" and a black and white specular layer. This is quite challenging, especially if the light source color is unknown. Existing methods handle this by combining color information across the image, differentiating between global and local approaches [40] . Global methods, like those by Klinker et al. and Tan and Ikeuchi, rely on explicit segmentation or known light source color. Local methods, on the other hand, focus solely on local interactions, assuming known light source color. Examples include iteratively reducing the specular component by analyzing neighboring pixels and minimizing an error function based on local variations.

This paper introduces a general framework using continuous-domain partial differential equations (PDEs) to formalize the concept of "local interactions" for specular/diffuse separation. [11] This method selectively shares color information between nearby image points through multi-scale erosion, adapting to both textured and untextured surfaces. The framework is extended to videos, incorporating motion information as an additional clue.

In practical applications, the paper showcases results on high-resolution lab images and 8-bit internet images, demonstrating robustness to artifacts like low dynamic range, JPEG compression, and unknown light source color. Results on videos highlight [8] the adaptability of the proposed method, even without explicit optical flow information.

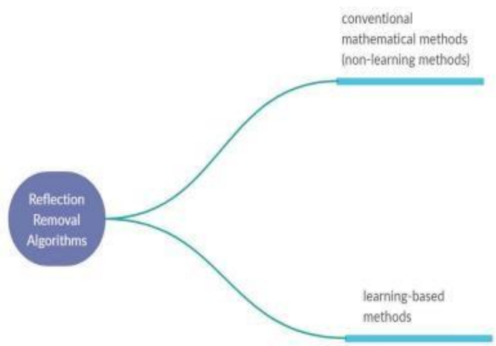

Figure 1: Classification of reflection removal algorithms (learning and non-learning methods).

Figure 1 shows there are essentially two primary classifications for reflection removal algorithms those based on learning techniques and those based on non- learning techniques.

2.APPLICATION AREAS

The few applicable areas of Specular Reflection Removal are as follow:

A.Learning Methods

These methods leverage the capabilities of machine learning, specifically focusing on deep learning techniques. They involve training algorithms on large datasets that include images with and without reflections. A popular technique involves employing convolutional neural networks (CNNs) [37]. In the prevalent paradigm of supervised learning, algorithms are trained to establish a mapping between input images and their respective versions free from reflections[14]. Generative adversarial networks (GANs) are also employed, introducing a generative model to produce reflection-free images and a discriminative model to evaluate the quality of the generated results.

B.Non-Learning Methods

Contrary to learning methods, non-learning approaches do not rely on training on extensive datasets. Instead, they often leverage mathematical models, assumptions about physical characteristics, or image processing techniques[17]. Model-based methods utilize predefined rules and assumptions about reflection properties, while segmentation-based techniques identify and separate reflection regions based on features like color, texture, or motion. Conventional image processing methods, including filtering and morphological operations, are frequently employed in non-learning approaches, offering a rule-based strategy for eliminating reflections.

Recent techniques based on image processing are also commonly employed in non-learning methods. Filtering, morphological operations, and other rule- based approaches are applied to reduce or eliminate reflections based on predefined criteria.

3.RESEARCH METHODOLOGY

Few of the Research Methodology are listed below

A.Planning

As far as we know, no one has done a thorough review of the research on using deep learning for [7] single-image reflection removal. In fact, this might be one of the first comprehensive reviews out there! So, it's the perfect time to gather and analyze all the existing studies in this area.

Formulation of the Research Protocol This review stands apart from the crowd thanks to its rigorous, protocol-driven approach. We scoured various databases like a tireless detective, then meticulously filtered results using strict criteria and quality checks. Our laser-focused research questions, crafted with precision, served as the guiding stars for the entire review, shaping its framework and goals.[12] This systematic journey ensures the information presented is trustworthy and relevant, offering a roadmap for anyone navigating this field.

Research Inquiries The primary aim of our systematic review is to pinpoint and scrutinize scholarly works employing deep learning methodologies for the removal of reflections in single images. Our pursuit of related research papers across diverse databases is geared towards achieving this overarching goal, giving rise to specific research questions. [13] These inquiries, along with their detailed explanations, are encapsulated in Table 1, outlining the focal points of our investigation.

Criteria for Inclusion and Exclusion Establishing clear methods is important to ensure that our examination focuses exclusively on research papers directly relevant to our topic. To achieve this, we devised five inclusion and five exclusion criteria, outlined in Tables 2 and 3, respectively. [15] Our initial keyword-based search yielded a pool of 1600 research papers related to our subject, with duplicate papers promptly removed.

Table 1: Research questions

No.	Questions	Descriptions
RQ1	What is the distribution of the selected research articles over the last seven years and their types?	Answering this question will give an overview of the type and publication year of considered papers in Reflection Removal.
RQ2	What datasets/databases are used to train the proposed deep learning model in considered publications?	Available datasets/databases with enough data are one of the most considerable factors in training deep learning algorithms.
RQ3	What datasets/databases are used for conducting experiments on single-image reflection removal?	Available datasets/databases with enough data are one of the most considerable factors in testing deep learning algorithms.
RQ4	What are the architectures of the proposed reflection removal networks in each paper?	Answering this question will give researchers an overview of the latest trends in applying deep learning algorithms in reflection removal.
RQ5	What quantitative metrics have been used to accredit the efficiency of the proposed deep learning techniques?	Answering this question will give researchers an overview of the utilized quantitative metrics in the field.
RQ6	What are the current limitations and challenges in this research field?	Answering this question will guide new researchers in potential future projects.
RQ7	What are the possible future works and directions in the single-image reflection removal field via deep learning techniques?	Answering this question will guide new researchers in potential future projects.

B.Quality Assessment Rules(QARs)

Quality Assessment Rules (QARs) serve as a frameworkfor evaluating the overall quality of selected research articles [59]. These criteria are instrumental in identifying and including research of the highest caliber. The application of these 10 rules is detailed in Table 4, where each rule contributes 1 point out of a sum of 10. [16] Points are assigned based on the thoroughness and comprehensiveness of each answer a complete and comprehensive answer earns 1 point, above normal earns 0.75, average earns 0.5, below average earns 0.25, and an unanswered question receives 0 points. The cumulative points for each research paper are tallied, and inclusion in this systematic review requires a total of 7 points or more, signifying a high-quality contribution

C.Conducting

In the paragraph of the systematic review process, our focus shifted to conducting an extensive search across online databases and digital libraries[31]. Employing carefully crafted search strings and keywords was integral to identifying the most relevant articles and research studies for inclusion in the systematic review.

The initial step in the phase of research involves systematically exploring digital libraries, databases, and scientific search engines to recognize the most pertinent articles. To achieve this objective, we conducted thorough searches on widely used online platforms and digital repositories, including IEEE Xplore, Science Direct, SpringerLink, Google Scholar, and the ACM Digital Library [18]. The terms selected for this search were

- Deep Learning
- Neural Network
- Convolutional Neural Networks
- [8] Single-image Reflection Removal

With the keywords defined above, multiple keywords and search strings that are made with logical operators were constructed in order to enhance the search results. The multiple keywords and search strings used for the SLR are mentioned below

- ‘‘reflection removal’’ AND ‘‘deep learning’’
- ‘‘reflection removal’’ AND (‘‘deep learning’’ OR ‘‘neural network’’)
- ‘‘reflection removal’’ AND ‘‘CNN’’

D.Image inpainting

Image inpainting, as pioneered by Criminisi et al. [27], involves a foundational approach using exemplar-based methods. Their technique prioritizes the repair of damaged regions by considering boundary information, selecting sample blocks from the image source area that closely match the target region. Expanding on this concept, Yin et al. [28] introduced refinements to the inpainting process. They proposed a more sophisticated priority function by integrating both curvature and color information of pixels, aiming for a nuanced and accurate restoration of damaged areas.

A subsequent improvement by Jing et al. [29] addressed challenges regarding to the confidence term in inpainting methods. They focused on suppressing the rapid decline of this term, contributing to the overall effectiveness of image inpainting. These advancements collectively showcase the evolution of inpainting techniques, from classic exemplar-based approaches to more sophisticated methods that consider curvature, color information, and confidence term dynamics for enhanced results.

E.Image classification

In image classification for specular reflection removal using Partial Differential Equations (PDEs), the focus is on categorizing pixels as either specular or non-specular based on their properties. PDEs provide a mathematical framework to model the distribution and behavior of specular reflections, aiding in the classification process and facilitating their targeted removal from images.[19] This approach enables a systematic analysis of reflection characteristics, contributing to the development of effective algorithms for enhancing image quality by mitigating the impact of specular reflections.

$$I = \begin{cases} I_h \; T_1 > t_1 \\ I_m - t_1 < T_1 < t_1 \\ I_l \; T_1 < t_1 \end{cases} \tag{1}$$

$$T_1 = \frac{l_a - L_a}{l_a} \tag{2}$$

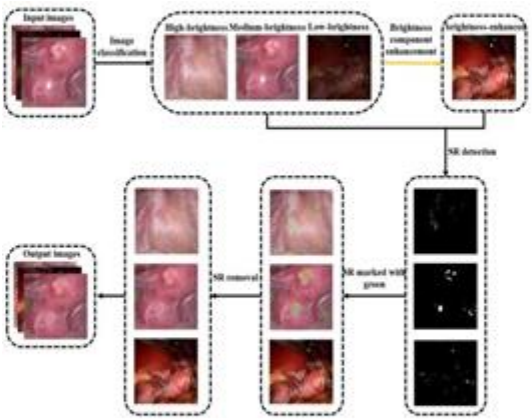

Figure 2: Schematic of the proposed methods

Figure 2 shows already proposed methods for eliminating specular reflections.

F.Specular reflection detection

Specular detection is a crucial aspect of image processing, especially in computer view applications where accurate scene understanding is essential [33]. Specular reflections, characterized by intense highlights on surfaces, can distort theinterpretation of scenes and hinder subsequentanalysis. Detecting specular reflections involves identifying bright spots in images that exhibit characteristics indicative of specular behavior. various strategies are employed for speculardetection, ranging from traditional image processing techniques to more advanced methods and learning methods. Traditional methods often rely on analyzing intensity, color, or texture patterns.[20] For instance, specular reflections tend to have high intensity and distinct color compared to their surroundings. These features can be exploited to develop algorithms that differentiate specular from non-specular regions[32]. On the other hand, machine learning-based approaches utilize trained models to recognize specular reflections. These models learn patterns and features from annotated datasets, allowing them to generalize and identify specular regions in new images. Efficient specular detection is fundamental to many computer vision tasks, including image enhancement, object recognition, and scene reconstruction.

$$\sigma_g = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(x_i - \mu_g\right)^2},\; \mu_g = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{3}$$

$$\sigma_b = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(x_i - \mu_b\right)^2},\; \mu_b = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{4}$$

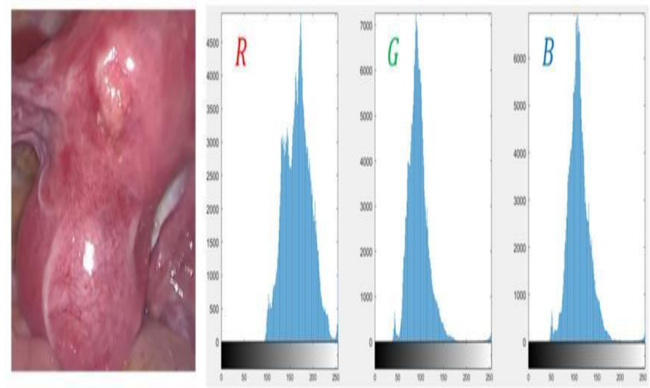

Figure 3: Histogram results. From left to right are the original image; red component histogram; green component histogram; blue component histogram

Among them, n is count of image pixels, x□ is the current pixel value, μ□, μ□are the mean values of G and B channel components respectively[21]. The proposed adaptive threshold function Th is defined as

$$Th = \max(g, b) - \tau \times \frac{\sigma_g + \sigma_b}{2} \tag{5}$$

$$\tau = \begin{cases} 0.3 & I = h_d \\ 0.8 & I = m_d \\ 1.1 & I = lv_d \end{cases} \tag{6}$$

The adaptive threshold function (Equation 5) is defined as the maximum intensity value between the green (g) and blue (b) channels subtracted by τ times the average standard deviation of the two channels. The adaptive weight τ is conditionally set based on three brightness levels 0.3 for high brightness (hd), 0.8 for medium brightness (md), and 1.1 for low brightness (lvd) images (Equation 6) this research implies that the threshold accommodates variations in image brightness, thereby enhancing the precision of specular reflection detection in endoscopic images. The parameter τ is empirically determined through extensive statistical experiments, providing optimal adaptability to brightness changes in the endoscopic image

4.PDE FOR REMOVING SPECULAR REFLECTION

Partial Differential Equations (PDEs)[22] plays a crucial role in addressing and mitigating specular reflections in images due to their ability to offer a mathematical foundation for understanding and modifying image characteristics. The utilization of PDE- based approaches in specular reflection removal is motivated by several factors, including

A.Mathematical formalism

Partial Differential Equations (PDEs) provide a robust mathematical structure for elucidating the characteristics of images. They enable the creation of differential equations that succinctly represent the changes in image properties across both spatial and temporal dimensions

B.Edge-preseving properties

PDE-based methods can be designed to be edge-preserving, meaning that they are effective in maintaining the integrity of edges and boundaries in an image.[34] This is important for specular reflection removal, as it helps prevent the loss of important details.

C.Incorporate of image constraints

PDE-based methods can incorporate various constraints based on the physics of light reflection and the properties of materials.[23] This allows for the development of algorithms that consider the expected behavior of light on different surfaces.

D.Adaptibility of image content

PDEs can be adapted to the specific content of an image, allowing for flexibility in handling different types of specular reflections. This adaptability is crucial in scenarios where the characteristics of reflections may vary widely

5.RESULTS

Testing the new methods involved feeding them images and videos from both lab settings and the wild web. For pictures where the light source was known or at least suspected, they were initially transformed into special color space called SUV (think Specularity, Uniformity, and Variability). Then, few mathematical equations was being implemented and this transformed space to figure out the image's shiny (specular) and rough (diffuse) parts.[35] To separate these components, the researchers used a fancy math tool called a multi-scale erosion partial differential equation (PDE). Imagine this as a special filter that gradually peels away the specular reflections, like gently untangling threads. They kept adjusting the filter until the changes became tiny, revealing the two components in all their glory.

It even worked on videos that did not require any extra data about how things were moving. These results suggest these methods could be used for all sorts of practical image and video processing tasks.

But there's a wrinkle using multi-scale erosion can be a bit messy mathematically. The equations involved are like cranky teenagers – sometimes they throw tantrums and create sudden jumps or "shocks" in the solution. To handle these shocks, the researchers borrowed some tricks from other fields, like

- Morphological derivatives some of the innovative images are done to smooth out image structures while keeping the important bits intact, like a gentle massage for the image.
- Viscosity solutions These add a kind of "regularization" term to the equations, like a calming voice that helps keep the math from going haywire.

By using these techniques, the researchers were able to get clear and stable results, even with tricky images. Its an huge move to forward for using PDEs in image processing, opening doors for more robust and reliable image analysis tools.

Figure 3 paints a clear picture of the proposed method's success. It showcases results from both controlled lab images and "wild web" downloads, with an assumed light source for the latter. Handling sudden jumps, called "shocks," in the equations is key to using [24] PDEs for separating specular and diffuse components. This method tackles this challenge head-on, paving the way for more reliable and robust image analysis techniques.

Think of PDEs as powerful tools for image processing, like magical brushes that can erase unwanted specular reflections. These reflections are distracting shinning image that flashes light bounces directly off a surface. Removing them not only makes the image prettier but also helps us understand what's really going on this picture .The new method shines, literally, in its ability to deal with tricky "shocks" that can mess up the process. By overcoming this hurdle, it opens doors for more dependable and accurate image analysis methods.

One approach to specular reflection removal using PDEs is to use a multi-scale erosion PDE. This PDE gradually erodes the image, preferentially removing the bright specular

Another approach to specular reflection removal using PDEs is to implement viscosity solution. Viscosity solutions are a type of PDE solution that is specifically designed to handle discontinuities. In the context of specular reflection removal, viscosity solutions will provide a smooth out the edges of specular highlights and implementing proactive defense strategies the diffuse components.

PDE-based methods[24] for specular reflection removal have several advantages over modern methods over traditional one, such as thresholding and filtering. PDEs are able to adapt to local image features and can handle a wider range of specular reflection phenomena. Additionally, PDEs can be implemented efficiently using numerical methods

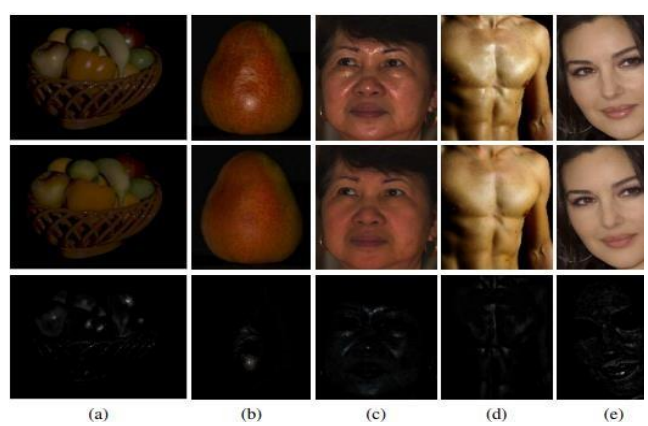

Figure 4: Separation Image

Figure 4 shows Results of the image separation process are presented in three rows the top row displays the original input images, the middle row shows the isolated diffuse components, and the bottom row exhibits the recovered specular components. Equation 19 is uniformly applied across all cases due to its natural adaptability to both textured and untextured surfaces. The input images in (a, b) are 12-bit images acquired in a controlled laboratory environment with a known illuminant color. In case (c), the illuminant color was unknown and assumed to be white. Additionally, 8- bit JPEG images from the Internet were used in cases (d, e), assuming a white illuminant color and a gamma of 2.2. Despite potential sources of noise, including unknown illuminant colors and compression artifacts, the methods successfully recovers both diffuse and specular components

Figure 5: Comparison to ground truth

Figure 5 shows Comparison to ground truth. Left input image. The image above showcases a visual comparison between the original image, the accurate diffuse component captured using linear polarizers, and the diffuse component reconstructed using anisotropic multiscale erosion. [26] This comparison is crucial for evaluating the importance of the erosion method in accurately replicating the ground truth diffuse component.

The ground truth image acts as a reliable benchmark, allowing for a precise assessment of how well the erosion method preserves and separates the diffuse elements within the image.[27] This analysis provides valuable insights into the method's ability to handle specular reflections effectively, ultimately determining its success in specular reflection removal using Partial Differential Equations (PDE).

The specular reflection results demonstrate the importance of the proposed method in isolating specular components from input images. By leveraging anisotropic multiscale erosion within the framework of Partial Differential Equations (PDE), the approach successfully recovers specular reflections.[28] This is evident in the distinct and accurate representation of specular components, showcasing the method's robustness in addressing specular reflections in diverse scenarios .Specular reflection removal is a critical step in image processing, aiming to eliminate or minimize unwanted reflections of light that obscure underlying details.[30] Traditional image processing techniques for specular reflection removal include thresholding, filtering, morphology, and partial differential equations (PDEs). [36]Identifying specular regions accurately can be challenging, especially in complex images with varying illumination. Preserving diffuse components while removing specular reflections is crucial to retain essential image information.[38] Handling varying illumination conditions poses a challenge in developing a universal specular reflection removal method.

Specular reflection removal enhances image quality and facilitates image analysis in medical imaging, product inspection, and robotics. Material analysis involves studying surface properties like roughness and texture using specular reflection separation.

6.CONCLUSION

Seperating light introduces a concept of specular reflection [2] removal using PDE in images and videos, employing local spatial interactions through differential morphology and the mathematical concept.[39] The method preserves diffuse texture by eroding specular components enhanced by primary color and shading information. While Works best for simple surfaces with predictable lighting color, future improvements aim to incorporate additional cues like local shape. In experimental applications to VW iris images, the proposed method outperforms existing specular noise removal techniques, demonstrating superior performance in biometric applications.

In the systematic review of [9] single-image reflection removal using deep learning, the research team analyzed 1600 articles from 2015 to 2021. The selected 25 papers were scrutinized to address key questions, revealing insights into distribution, datasets, network architectures, evaluation metrics, challenges, and future directions in the field. The review underscores the growing importance of deep learning techniques for [12] single-image reflection removal and provides valuable perspectives for researchers entering this domain.

Moreover, experimental applications of the method in VW iris images demonstrate its superior performance in specular noise removal compared to existing techniques. The proposed approach, utilizing morphological dilation and region-filling techniques, outperforms linear interpolation methods, as evidenced by higher Structural Similarity Index (SSIM) values. This underscores the method's potential suitability for applications in biometric settings, particularly in the context of VW iris image processing.

The systematic review on [13] single-image reflection removal using deep learning and neural networks provides comprehensive insights into the evolving landscape of the research domain. Analyzing 1600 articles from 2015 to 2021, the review identifies trends in distribution, datasets, network architectures, evaluation metrics, challenges, and future directions. The selected 25 papers showcase the growing significance of deep learning techniques in addressing the complexities of [29] single-image reflection remov

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