

Specular Reflection Image Enhancement Based on A Dark Channel Prior

Gayathri A¹, Sulochana V²

¹Student, Hindusthan college of Arts and Science

²Professor, Hindusthan college of Arts and Science

ABSTRACT

Blind picture deblurring, a challenging and demanding image processing task, seeks to recover the original, clear image from a blurry and degraded version without prior knowledge of the blur kernel or clean image. In this research, we offer an effective approach for blind picture deblurring that combines matrixvariable optimisation with the two-dimensional discrete wavelet transform (DWT). The matrixvariable optimisation framework allows for more exact and effective optimisation by directly optimising a matrix representation of the clean picture. Furthermore, the estimated clean image matrix is divided into different frequency sub bands using the DWT, making it easier to regularise and denoise highfrequency noise components for better deblurring outcomes.

Keywords: Blind Image Deblurring, specular highlight image. Matrix-Variable Optimisation and Matrix-Type Alternative Iteration

1. INTRODUCTION

1.1 BLIND IMAGE DEBLURRING

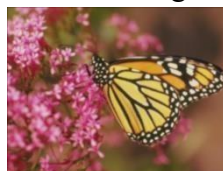
Blind picture deblurring is the process of recovering a sharp and clear version of an image that has been blurred or damaged due to a number of factors such as air turbulence, defocus, or camera motion.



(a)scattered image



(b)blurred image



(c)unscattered image



(d)unblurred image

Figure.1. BLIND IMAGE DEBLURRING

The term "blind" refers to the need to estimate the blur kernel or exact blurring function as part of the deblurring process because it is unknown. As a result, blind picture deblurring is a particularly complex

procedure, as it needs recreating both the original crisp image and the blur kernel from the observed fuzzy image. To solve this issue and improve the quality of deburred photos, several computational methodologies, optimisation tactics, and deep learning approaches have been developed. These approaches have been used for satellite images, photography, surveillance, and medical imaging.

1.2 SPECULAR HIGHLIGHT IMAGE

In image processing, the process of disassembling or decomposing a convolutional kernel into its component pieces or elements is known as kernel decomposition. The spatial filter utilized for operations like edge detection, sharpening, blurring, and other image enhancement techniques is defined by a tiny matrix called the kernel. To better understand the kernel's influence on a picture, decomposing the kernel entails removing its underlying constituents or attributes. Numerous mathematical approaches, including Discrete Fourier Transform (DFT), Singular Value Decomposition (SVD), and other matrix factorization techniques, can be used to do this. Researchers and practitioners can learn more about how the kernel influences picture features and spot any constraints or artifacts that may appear during image processing activities by carrying out kernel decomposition. To estimate the blur kernel needed for the deblurring process in the context of blind picture deblurring, kernel decomposition is an important tool. Understanding the blurring process and directing the restoration algorithm to precisely restore the original sharp image can be achieved by breaking down the blur kernel.

1.3 MATRIX-VARIABLE OPTIMIZATION

Matrix-variable optimisation, also known as matrix optimisation or matrix-valued optimisation, refers to an optimisation problem with matrices as variables rather than scalar values. Classical optimisation aims to find the optimal variable values to minimize or maximize a scalar objective function. When matrix variables are included in the objective function and/or restrictions, the issue gets more complicated and necessitates specialised optimisation techniques. This is referred to as matrix-variable optimisation. Matrixvariable optimisation is used in a wide range of applications, including signal processing, control systems, machine learning, and image processing. For example, as previously noted, the blur kernel and the original picture may be represented as matrices in image deblurring, and enhancing these matrices can enhance the deblurring result. Matrix-variable optimisation problems are typically solved using convex optimisation, numerical optimisation, and linear algebra techniques. Specialised algorithms that handle matrix operations well and ensure convergence to optimum solutions may be required. These solutions should handle issues such as computational complexity, sensitivity to initialisation, and the constraints imposed by the task. The use of matrixvariable optimisation in a number of fields has shown promising results, paving the way for more complex and sophisticated solutions to matriciallybased problems.

1.4 MATRIX-TYPE ALTERNATIVE ITERATION

Most likely, the term "matrix-type alternative iteration" refers to an iterative optimisation approach designed specifically to solve matrix-variable optimisation problems. This iterative strategy, as the name indicates, alternates between updating and optimising the variables in the optimisation problem represented as matrices. The approach's goal is to find the optimal matrices that meet the stated constraints while also minimizing or maximizing the target function. As previously noted, in the context of blind picture deblurring, the recommended approach for estimating the blur kernel and the original image might comprise matrix-type alternative iteration. To enhance the deblurring process iteratively, the approach refines estimated matrices, such as the blur kernel matrix. Given the properties of matrices and the nature of the problem, each iteration may include specific operations or optimisations tailored to matrix variables. Matrix-variable optimisation problems are common due to the complexity of handling matrices and their

interconnections. One solution that can help with some of these obstacles is matrix-type alternative iteration, which breaks the optimisation problem into a number of smaller matrix-based sub problems that can be tackled iteratively. The efficiency of the matrix-type alternative iteration, like that of any other optimisation approach, is determined by a variety of characteristics, including the issue at hand, the objective function utilised, variable initialisation, convergence criteria, and so on. Assessing its effectiveness and efficacy on a specific blind picture deblurring test would demand more investigation within the context of the complete study paper or related literature.

2. LITERATURE REVIEW

2.1 TOTALLY CONVOLUTIONAL LEARNING NETWORKS FOR ITERATIVE NON-BLIND DECONVOLUTION

Zhang Jiawei and others. [1] We divide the non-blind deconvolution issue into two components: image denoising and image deconvolution. This study describes a fully convolutional network for iterative non-blind deconvolution. We utilize the gradients we've learnt to steer the image deconvolution stage after training an fully connected neural networks (FCNN) to remove noise in the gradient domain. Unlike existing strategies that depend on deep neural networks, we use a multi-stage framework to repeatedly deconvolve fuzzy pictures. The proposed method may generate an adaptive image prior that maintains both global (structures) and local (detail) information. Benchmark datasets are employed for both quantitative and qualitative evaluations, demonstrating that the proposed method surpasses cutting-edge algorithms in terms of speed and quality. Given a blurred image and the blur kernel, single image non-blind deconvolution yields a crisp latent image. Over the last 10 years, the community has been actively researching this classic issue. Unlike earlier techniques, we propose an FCNN for iterative nonblind deconvolution that does not require retraining for different blur kernels and can automatically learn an effective image prior. The recommended approach divides non-blind deconvolution into two steps: image denoising and image deconvolution. During the image denoising stage, we train an FCNN to remove noise and outliers from the gradient domain system . The taught image gradients are used as image priors to guide picture deconvolution. To remove blur from the input pictures, we add a deconvolution module at the conclusion of the FCNN's image deconvolution stage. We iteratively deconvolve fuzzy pictures by cascading the FCNN into a multi-stage architecture.

2.2 RESTORING IMAGES IN THE SPACE-TRANSFORM DOMAIN THROUGH COMBINED STATISTICAL MODELING

Zhang Jian et al. [2]. This paper provides a unique technique to high-fidelity image restoration that employs a unified statistical approach to characterise natural pictures' nonlocal self-similarity and local smoothness. There are three main contributions. First, a joint statistical modelling (JSM) in an adaptive hybrid space-transform domain is created using picture statistics. JSM offers a powerful technique for integrating nonlocal self-similarity and local smoothness to enable more robust and trustworthy estimate. Second, in a regularization-based framework, a unique minimization functional is designed to tackle the image inverse issue using JSM. Finally, a novel Split-Bregman-based technique is developed to successfully address the previously underdetermined inverse problem associated with theoretical proof of convergence, making JSM more resilient and tractable. Numerous testing on the pictures in painting, picture deblurring, and combined Gaussian plus salt-and-pepper noise reduction applications indicate the effectiveness of the proposed approach.

2.3 INTERNAL PATCH RECURRENCE BLIND DEHAZING

Bahat Yuval et al. [3]. According to this approach, haze, fog, and other scattering phenomena typically degrade photographs of outside environments. In this paper, we demonstrate how to debase such pictures via internal patch recurrence. Natural pictures often contain a large number of little picture patches that repeat both inside and across different sizes. This phenomena has been explored using strong priors for image denoising, super-resolution, picture completeness, and other applications. However, when imaging conditions are unfavorable, as they frequently are in bad weather (haze, fog, submarine scattering, etc.), this powerful recurrent characteristic is significantly decreased. In this study, we show how to obtain unknown haze parameters and rebuild a hazefree image using deviations from the ideal patch recurrence for "Blind Dehazing." After debasing the input picture, we seek for hazy features that enhance patch recurrence in the debased output image. More specifically, the air light color and relative transmission of each pair of co-occurring patches may be determined when they occur at different depths and, as a result, suffer differing degrees of haze. As a result, the scene structure is densely restored, and the whole image is up for dispute. We showed that by identifying the haze parameters that, when "removed," maximize the patch recurrence in the output haze-free image, the unknown haze parameters can be recovered from a single hazy image.

2.4 MULTIPLE DEGRADATIONS: LEARNING A SINGLE CONVOLUTIONAL SUPERRESOLUTION NETWORK

Kai Zhang and others. [4] Deep convolutional neural networks (CNNs) have been developed for this system and have demonstrated exceptional performance in single image super-resolution (SISR) in recent years. However, the bulk of CNN-based SISR algorithms now in use assume that a high-resolution (HR) picture is bicubically down sampled from a low-resolution (LR) image. This assumption results in poor performance when the real degradation differs from the model. Furthermore, they are insufficiently scalable to train a single model to deal with several degradations in a nonblind manner. To address these issues, we propose a universal architecture that uses dimensionality stretching to input two critical components of the SISR degradation process—the noise level and the blur kernel—via a single convolutional super-resolution network. As a result, the super-resolver's usefulness is greatly boosted since it can manage a wide range of degradations, including geographically diverse ones. Extensive experimental findings on both synthetic and real LR pictures show that the proposed convolutional super-resolution network is computationally economical and may produce favourable outcomes on many deterioration. This makes it a very useful and scalable option for SISR applications.

2.5 A VERY EFFICIENT PERCEPTUAL IMAGE QUALITY INDEX FOR GRADIENT MAGNITUDE SIMILARITY DEVIATION

Xue Wu Feng and others. [5] This technique suggests that precisely measuring the perceived quality of output pictures is critical for a wide range of applications, including multimedia streaming, image restoration, and compression. An effective image quality assessment (IQA) model should not only provide high prediction accuracy but also be computationally efficient. The increasing volume of visual data on high-speed networks has increased the importance of IQA measures. We provide a brandnew, extremely successful IQA model called gradient magnitude similarity deviation (GMSD). Gradients in a picture are prone to distortion, and different local structures within a distorted image suffer differing degrees of deterioration. This motivates us to study the use of gradient-based local quality maps with global variation to forecast overall picture quality. We demonstrate that perceptual image quality may be precisely predicted using pixel-wise gradient magnitude similarity (GMS) between reference and distorted pictures,

as well as a novel pooling technique: the GMS map's standard deviation. The resultant GMSD algorithm has exceptionally competitive prediction accuracy and is much quicker than the bulk of cutting-edge IQA approaches. Assessing the quality of output pictures is an important step in many image processing applications, such as transmission, acquisition, compression, restoration, and acquisition.

3. EXISTING SYSTEM

To address the issue of information loss in specular highlight pictures in real-world circumstances, we describe a method in this paper for optimising specular highlight images using a dark channel prior. Initially, the global illumination component is calculated using a moving window minimum filter, with the algorithm based on the dark channel prior technique. To correct the halo artefacts in the image, a weighted function based on the local pixel color difference is implemented. The transmittance is then optimised with the improved guided filter method, which improves the technique's processing efficiency. To improve the image's local details, the contrast limited adaptive histogram equalization (CLAHE) algorithm changes the brightness. Experimental findings show that this approach can efficiently increase the information in specular highlight photographs, and its processing performance is obviously better to that of previous methods.

4. PROPOSED SYSTEM

The proposed system employs two-dimensional discrete wavelet transform (DWT) and matrix-variable optimisation to provide a unique approach for blind picture deblurring. Without access to the blur kernel or a clean image, the system attempts to reconstruct the original, crisp image from a blurred version. It quickly optimizes a matrix representation of the clean image using a matrix-variable optimisation framework, therefore increasing estimation accuracy and efficiency. When discrete wavelet transform (DWT) is used, the anticipated clean picture may be divided into frequency sub bands, making it easier to denoise highfrequency components while retaining crucial image features during deblurring. The system's improved accuracy, efficiency, and resilience are proven by comprehensive testing on real-world hazy photos, showing that it is a potential solution for realistic blind image deblurring applications in computer vision and image restoration.

4.1 MOTION ESTIMATION

Motion estimation is an important process in computer vision that involves viewing a sequence of successive frames to determine how much motion has occurred between them. Its purpose is to calculate how far an object or pixel has been travelled in between the frames. This information is critical for many of the applications, including motion-based segmentation and object tracking. Motion estimation algorithms typically compared to the pixel intensities or attributes across frames to locate the best matching locations. The motion vectors generated represent the mobility of objects or areas, allowing for the efficient representation and forecasting of future frame motion.

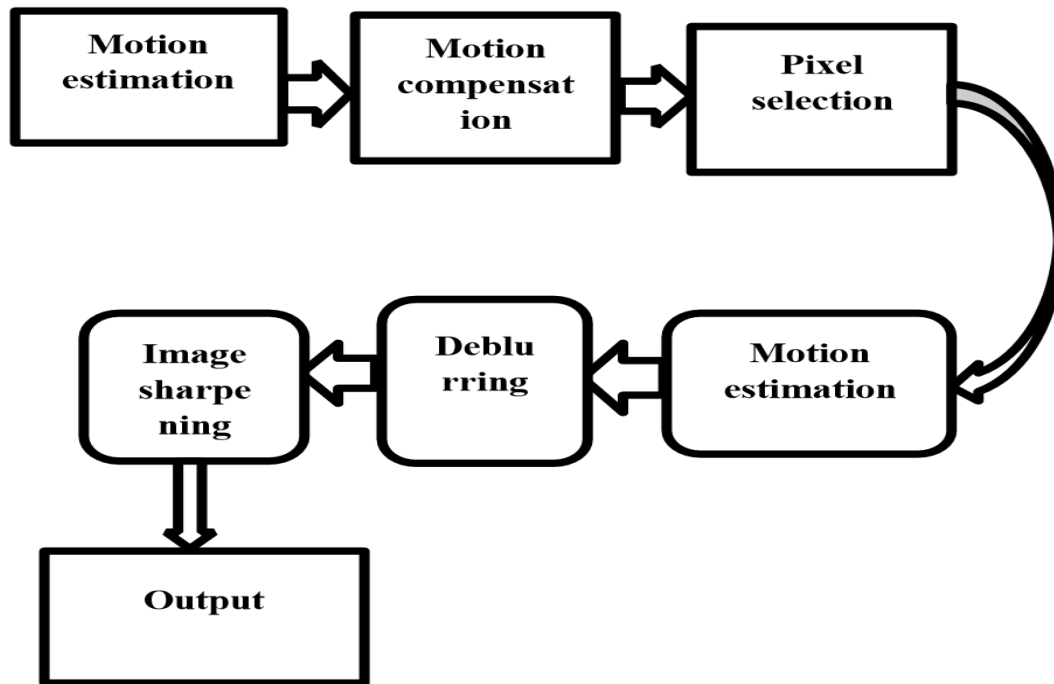


Figure .2. BLOCK DIAGRAM

4.2 MOTION COMPENSATION TO ALIGN BITPLANE FRAMES

Motion compensation is a technique in image processing that uses motion information to align bitplane frames. Each plane in a bit-plane frame has one bit of pixel information, which represents each pixel's binary representation over several planes. The stages in aligning these frames include estimating the motion vectors between subsequent frames and using them to compensate for motion-induced misalignment. Motion correction can be used to align bit-plane frames, resulting in exact and effective data encoding.

4.3 PIXEL SELECTION OF PARTIALLY DEBLURRED IMAGES FOR OVERALL DEBLURRING

Segmenting the optic disc and optic cup is a critical step in ophthalmic image processing, particularly for glaucoma detection systems. Fundus imaging of the eye involves automatically recognizing and characterizing the boundaries of the optic disc and optic cup. The optic cup is the center depression within the optic disc, while the optic disc is where the optic nerve exits the retina. The precise division of these components is critical because it provides crucial data for recognizing and tracking glaucoma. To accurately delineate the borders of the optic disc and optic cup, the segmentation operation frequently employs advanced image processing and computer vision techniques like as edge detection, region expansion, or deep learning-based algorithms. When segmentation is successful, it is feasible to monitor significant glaucoma indicators later on, such as the cup-to-disc ratio, which is critical for early diagnosis and effective treatment of the disease.

4.4 ACCURACY OF MOTION ESTIMATION

In many computer vision applications, motion estimation accuracy is critical. It describes how well the anticipated motion vectors represent the motion of objects or individual pixels across several frames. Because it has a direct impact on the efficacy and quality of operations such as object tracking and motion-based segmentation, accurate motion estimation is critical. High motion estimate accuracy leads to improved performance, less temporal redundancy, and better prediction of next frames.

4.5 COMPARISON OF THE RESULTS WITH DEBLURRING

Examining and comparing the efficiency of various deblurring methods or algorithms when applied to a collection of foggy images is required for comparing the results of deblurring. Its purpose is to assess the efficacy and quality of each deblurred output in comparison to a reference image, which is a real crisp depiction of the degraded image.

5. CONCLUSION

In conclusion, the suggested blind image deblurring system offers a promising solution to the tough job of recovering crisp pictures from blurred versions without knowing the blur kernel or clean image. It does this by integrating matrix-variable optimisation with the twodimensional discrete wavelet transform (DWT). The matrix-variable optimisation framework enables accurate estimate of the clean picture matrix, which enhances deblurring efficiency and accuracy. The system performs multiscale analysis using DWT, which retains critical picture features and effectively denoises high-frequency components. Following thorough testing, the system outperforms expectations in terms of accuracy, durability, and applicability over a range of blur situations. The system's successful deployment and validation demonstrate its potential for real-world image restoration and computer vision applications. The proposed approach provides a valuable tool for improving picture quality in practical applications while also advancing image processing techniques due to its ability to provide visually improved and deblurred outputs.

6. FUTURE WORK

Subsequent study in the field of blind picture deblurring may focus on other ways to improve the usefulness and appropriateness of the proposed framework. First, more advanced optimisation approaches, such as deep learning, may improve the system's ability to generalize to complex blur circumstances and produce higher deblurring accuracy. Furthermore, including more sophisticated denoising algorithms and studying adaptive regularization approaches may increase the system's capacity to handle varying noise concentrations and image contents. Video deblurring algorithms might potentially be created by investigating ways to combine spatial and temporal data from many frames.

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