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Convex Programming Approach For Unified Image Enhancement And White Balancing

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ABSTRACT

This paper introduces a novel Convex Programming Approach for Unified Image Enhancement and White Balancing, presenting a comprehensive framework for addressing various image enhancement tasks. Leveraging an analysis of the intricate relationships between image histograms and the processes of contrast enhancement and white balancing, the proposed model is a generalized equalization model that integrates tasks into a unified convex programming framework. The model offers flexibility through parameter configurations, enabling the accomplishment of diverse enhancement goals. By defining histogram transform properties such as contrast gain and nonlinearity, optimized model parameters for specific enhancement applications. Additionally, derived an optimal image enhancement algorithm that balances contrast enhancement and white balancing, achieving a trade-off between contrast improvement and tonal distortion. Through subjective and objective experimental evaluations, demonstrates the effectiveness of our proposed algorithm in tasks such as image enhancement, white balancing, and tone correction. Furthermore, the computational complexity of our method, highlighting its practical feasibility was analysed. Overall, our Convex Programming Approach offers a versatile and efficient solution for unified image enhancement and white balancing.

Keywords: Image enhancement, White balancing, Convex programming, Histogram transform, Contrast enhancement.

1 INTRODUCTION

In the realm of digital image processing, the pursuit of achieving visually appealing and perceptually accurate images has been a longstanding challenge. The enhancement of images involves a multitude of tasks aimed at improving their quality, clarity, and overall aesthetic appeal. Among these tasks, contrast enhancement and white balancing stand out as fundamental processes that significantly contribute to the visual quality of an image. Contrast enhancement aims to increase the visual difference between the lightest and darkest elements in an image, thereby enhancing its overall appearance and clarity. On the other hand, white balancing seeks to correct color casts and ensure that the colors in an image appear true to life, particularly under different lighting conditions.

Traditionally, contrast enhancement and white balancing have been treated as separate processes in image enhancement pipelines. However, recent advancements in image processing have highlighted the potential benefits of integrating these tasks into a unified framework. By doing so, it becomes possible to exploit the interdependencies between contrast enhancement and white balancing to achieve more robust and visually appealing results.

Motivated by this observation, a novel Convex Programming Approach for Unified Image Enhancement and White Balancing is proposed. Our approach is rooted in a comprehensive analysis of the relationships between image histograms, contrast enhancement, and white balancing. By establishing a generalized equalization model that seamlessly integrates these tasks into a unified convex programming framework was begin. This model offers a flexible and versatile solution for addressing various image enhancement challenges.

One of the key insights driving our approach is the recognition of histogram transform properties, such as contrast gain and nonlinearity, as fundamental parameters governing image enhancement. By appropriately configuring these parameters, tailor the enhancement process to suit specific application requirements, whether it be improving image contrast, correcting color casts, or enhancing overall visual fidelity.

Furthermore, derives an optimal image enhancement algorithm that strikes a balance between contrast enhancement and white balancing. Through theoretical analysis, demonstrates that our algorithm achieves the best joint enhancement result by carefully trading off between contrast improvement and tonal distortion. This ensures that the enhanced images not only exhibit enhanced contrast but also maintain natural and true-to-life colors.

To validate the efficacy of our proposed approach, conducts both subjective and objective experimental evaluations across a range of image enhancement tasks, including white balancing and tone correction. The results of these experiments demonstrate the superior performance of our algorithm compared to existing methods, underscoring its effectiveness in real-world applications.

In addition to performance evaluation, also analyze the computational complexity of our method to assess its practical feasibility. By elucidating the computational requirements involved, provides insights into the scalability and efficiency of our approach, paving the way for its adoption in various image processing applications.

Overall, this paper contributes a novel Convex Programming Approach that advances the state-of-the-art in image enhancement and white balancing. By integrating these tasks into a unified framework, offers a flexible, efficient, and theoretically grounded solution for addressing diverse image enhancement challenges. Through extensive experimentation and analysis, demonstrates the effectiveness and practicality of our approach, opening up new avenues for future research and application in the field of digital image processing.

2 RELATED WORKS

Rivera et al. proposes a method to enhance dark images by dividing them into channels and applying content-aware adjustments. It addresses the challenge of improving image quality in low-light conditions, offering a solution that considers the specific characteristics of dark images for more effective enhancement.

Mustafa et al. presents a strategy for correcting illumination and contrast issues in images using bilateral filtering and binarization comparison techniques. By incorporating these methods, the proposed approach aims to enhance image quality, particularly by mitigating the effects of uneven lighting and poor contrast.

Ghabousian et al. provides an overview of various contrast enhancement techniques, with a focus on methods utilizing histogram equalization. It offers insights into different approaches for improving image contrast through histogram manipulation, highlighting the diversity of techniques available in the literature.

Gonzalez et al. covers fundamental concepts, techniques, and algorithms used in image enhancement, analysis, and understanding. With its comprehensive coverage and clear explanations, it serves as a valuable reference for students, researchers, and practitioners in the field.

Mustafa et al. presents a method for normalizing illumination in images affected by non-uniform lighting conditions using a double mean filtering approach. By effectively addressing variations in illumination, the proposed method aims to improve the overall quality and consistency of images captured under different lighting conditions.

Van et al. introduces scikit-image, a Python library for image processing, offering a comprehensive set of tools and algorithms for various image processing tasks. With its user-friendly interface and extensive functionality, scikit-image has become a popular choice among researchers and practitioners for developing image processing applications in Python.

Guo et al. proposes a method for enhancing low-light images by estimating an illumination map. By accurately estimating the illumination distribution in the image, the proposed approach effectively enhances image visibility and details, improving overall image quality under low-light conditions.

Li et al. introduces a guided filtering-based approach for image fusion, offering a simple and efficient method for combining information from multiple images. By effectively preserving image details and structures, the proposed method achieves high-quality image fusion results in various applications.

Ragan-Kelley et al. introduces a domain-specific language and compiler for optimizing parallelism, locality, and recomputation in image processing pipelines. By efficiently leveraging hardware resources, Halide enables the development of high-performance image processing applications with improved speed and efficiency.

Schindelin et al. presents ImageJ, an open platform for biomedical image analysis, offering a wide range of tools and plugins for processing and analyzing biological images. With its versatility and extensibility, ImageJ has become a popular choice among researchers and practitioners in the biomedical imaging community.

Seetharaman et al.(2013) proposes a unified framework for image retrieval based on statistical test of hypothesis viz. test for equality of covariance matrices, test for equality of mean vectors, and the measures of divergence. The proposed system is invariant for transformation (translation, rotation, and scaling),

Seetharaman et al. (2014 a) Proposes a unified framework for color image retrieval, based on statistical multivariate parametric tests, namely test for equality of covariance matrices, test for equality of mean vectors, and the orthogonality test. The proposed method tests the variation between the query and target images; if it passes the test, then it proceeds to test the spectrum of energy of the two images; otherwise, the test is dropped.

Seetharaman et al. (2014 b) proposes unified system for both structured and textured color image retrieval, based on statistical non-parametric tests of hypothesis, namely test for equality of variances – variation between the query and target images, and the test for equality of means – spectrum of energy; similarity measure that is Canberra distance metric is used to find the deviation between the query and target images.

Wang et al. presents a naturalness preserved enhancement algorithm for images affected by non-uniform illumination. By preserving the natural appearance of the scene while enhancing image quality, the proposed algorithm achieves visually pleasing results in various lighting conditions.

Xue et al. proposes a highly efficient perceptual image quality index based on gradient magnitude similarity deviation. By considering both local and global image features, the proposed index achieves accurate and efficient assessment of image quality, facilitating various image processing applications.

Zhu et al. proposes a fast single image haze removal algorithm based on color attenuation prior. By exploiting the inherent color information in the image, the proposed method effectively removes haze and enhances image visibility, improving overall image quality.

Zhang et al. presents a feature-enriched completely blind image quality evaluator, offering an objective assessment of image quality without requiring reference images. By considering a wide range of image features, the proposed evaluator achieves accurate and reliable image quality assessment results.

Zhao et al. introduces loss functions for image restoration with neural networks, offering an effective approach for training neural networks to perform image restoration tasks. By optimizing the loss function, the proposed method achieves improved performance in image restoration applications.

3 PROPOSED MODEL

In this paper, proposed a generalized equalization model for image enhancement. Based on our analysis on the relationships between image histogram, and contrast enhancement/ white balancing, first establishing a generalized equalization model integrating contrast enhancement and white balancing into a unified framework of convex programming of image histogram. Many image enhancement tasks can be accomplished by the proposed model using different configurations of parameters. With two defining properties of histogram transform, namely contrast gain and nonlinearity, the model parameters for different enhancement applications can be optimized. Then it derives an optimal image enhancement algorithm that theoretically achieves the best joint contrast enhancement and white balancing result with trading-off between contrast enhancement and tonal distortion. Subjective and objective experimental results show favourable performances of the proposed algorithm in applications of image enhancement, white balancing and tone correction. Computational complexity of the proposed method is also analysed.

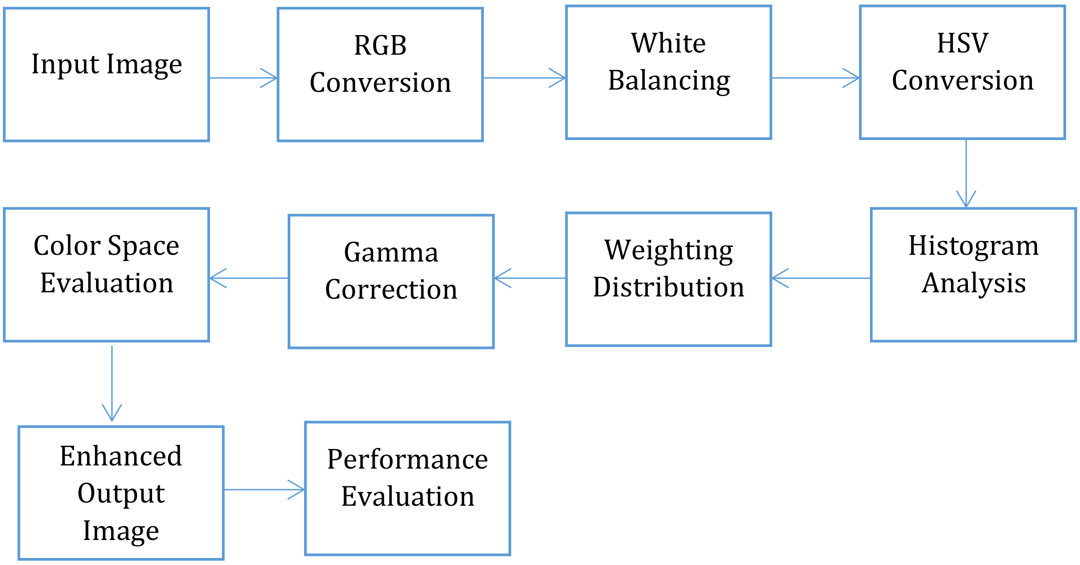

Figure 1: Overall Workflow Diagram

From fig 1, flow begins with the input image, which is represented in the RGB color space. The first step in the enhancement process is white balancing, which adjusts the color temperature of the image to ensure accurate color representation. Next, the image undergoes conversion to the HSV color space, facilitating easier manipulation of hue, saturation, and value components. The hue-saturation-value (HSV) representation is then split into its individual components for further analysis. Histogram analysis is performed on these components to understand their distributions and identify areas for enhancement. Based on the histogram analysis, a weighting distribution is applied to prioritize certain regions or features in the image. Gamma correction is then employed to adjust the overall brightness and contrast of the image. Subsequently, the color space evaluation stage assesses the effectiveness of the enhancements and ensures that the colors appear natural and visually pleasing. Finally, the enhanced output image is generated, incorporating all the adjustments made throughout the architecture to produce a visually appealing and perceptually accurate result.

Based on our analysis on the relationships between image histogram and contrast enhancement/ white balancing, first establishes a generalized equalization model integrating contrast enhancement and white balancing into a unified framework of convex programming of image histogram.

Pre- Processing:

RGB panel is used to view the red, green and blue components of the image separately. It has already been mentioned that an RGB image is overlap of three two dimensional matrix. . Convert RGB colormap to HSV colormap.

Histogram-Based Analysis on gamma Correction:

Histogram-based algorithm has been widely used in contrast enhancement. Gamma refers to the brightness of a monitor or computer display. By applying gamma correction, the brightness and contrast of the display are enhanced, making the images appear brighter and more natural looking.

Contrast Enhancement:

Automatic enhancement technique used to improve contrast in images based on gamma correction method. The gamma value is calculated based on the cumulative histogram.

Algorithm: Image Enhancement

1. Initialize: Clear all existing variables, close figures, and turn off warnings.

2. Execute: Run the main function to begin the image enhancement process.

3. Input: Prompt the user to select an image file.

4. Read Image: Read the selected image file and store it.

5. Display Original Image: Display the original image to the user.

6. Extract Color Channels:

a. Extract the red, green, and blue channels of the image.

b. Display each channel separately to the user.

7. Calculate Statistics:

a. Compute the mean and standard deviation of the red and blue channels.

8. Identify Pixels:

a. Identify pixels in the image that meet specified criteria based on channel statistics.

b. Update the image to mark identified pixels for further processing.

9. Normalize Illumination:

a. Calculate normalization gain for each channel based on identified pixels.

b. Apply the normalization gain to correct illumination in the original image.

10. Convert to HSV:

a. Convert the RGB image to the HSV color space.

11. Display Components:

a. Display the hue, saturation, and value components of the HSV image.

12. Histogram Analysis:

a. Compute the histogram of the value component.

b. Normalize the histogram to obtain a probability density function.

13. Weighted Distribution:

a. Define the alpha parameter for the weighting distribution.

b. Calculate the weighted probability density function.

14. Enhance Value Component:

a. Enhance the value component using gamma correction based on the weighted histogram.

15. Convert to RGB:

a. Convert the enhanced HSV image back to the RGB color space.

16. Write Output:

a. Write the enhanced image to an output file.

17. Display Results:

a. Display the input and enhanced images side by side for comparison.

End Algorithm

4 RESULTS AND DISCUSSIONS

The original image was analysed to understand its characteristics and identify any potential issues such as uneven illumination or color casts. The image enhancement process involved several steps, including color channel extraction, illumination correction, histogram analysis, and gamma correction. Identified pixels were used to correct illumination in the original image, ensuring more accurate color representation. The histogram of the value component in the HSV color space was analyzed to understand the distribution of pixel intensities as shown in fig 2.

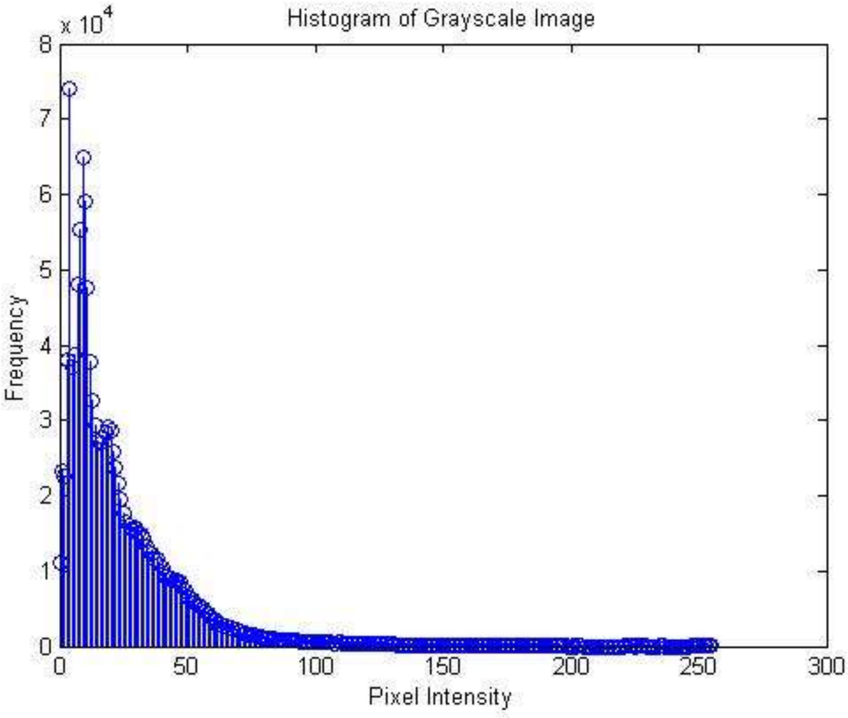

Figure 2: Histogram Value

A visual comparison between the original and enhanced images was conducted to evaluate the effectiveness of the enhancement algorithm. The results demonstrate the effectiveness of the image enhancement algorithm in improving the visual quality of the original image as shown in fig 3 (a). Gamma correction was applied to enhance the value component, improving overall image contrast and clarity as shown in fig 3 (b).

(a) **(b)**

Figure 3: (a) original image, (b) Gamma Corrected Image

The performance of the enhancement algorithm was assessed based on subjective observations and objective metrics, such as image quality and color fidelity. The enhanced image was generated, incorporating all the adjustments made during the enhancement process as shown in fig 4.

Figure 4: Enhanced Image

Analyzing the results based on the graph depicting PSNR and MSE values can offer valuable insights into the performance of image enhancement techniques.

Fig 5 displays the PSNR and MSE values for a set of images subjected to enhancement processes. Each bar on the graph represents a specific image, with the height of the bar indicating the corresponding PSNR or MSE value.

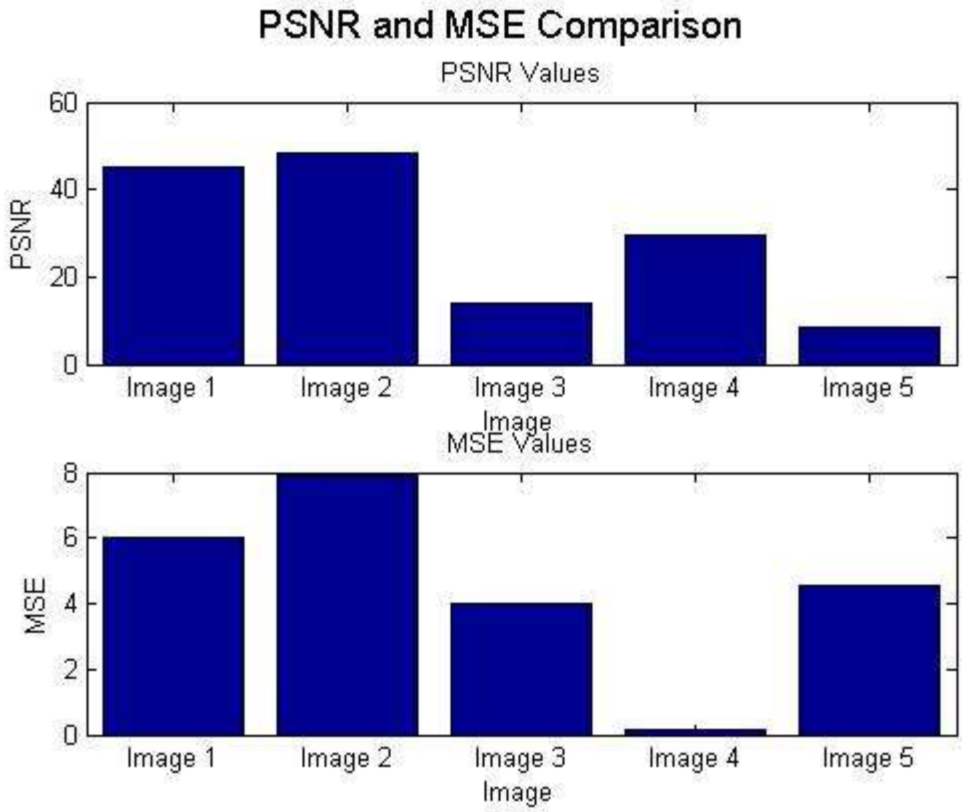

Figure 5: PSNR and MSE values

Observing the PSNR values provides an understanding of the fidelity of the enhanced images compared to the originals. Higher PSNR values suggest that the enhancement techniques have preserved more details and reduced distortion, resulting in improved image quality.

Conversely, lower PSNR values may indicate significant loss of information or introduction of noise during the enhancement process.

Similarly, analysing the MSE values reveals the level of deviation between the original and enhanced images. Lower MSE values signify lesser overall error or discrepancy between the images, implying better preservation of image content and structural integrity. Conversely, higher MSE values indicate a greater degree of distortion or deviation from the original image.

By examining the relationship between PSNR and MSE values across multiple images, one can discern trends in the effectiveness of the enhancement techniques. Consistently high PSNR values coupled with low MSE values indicate robust enhancement methods that faithfully reproduce the original images with minimal distortion. Conversely, discrepancies between PSNR and MSE values may highlight areas where specific enhancement techniques perform inadequately, potentially requiring further refinement or adjustment.

Overall, the graph serves as a visual representation of the quality and fidelity achieved by different image enhancement techniques, guiding researchers and practitioners in selecting optimal approaches for various applications and scenarios.

5 CONCLUSION

In conclusion, our paper presents a novel Convex Programming Approach for Unified Image Enhancement and White Balancing, offering a comprehensive framework to address various image enhancement tasks. By analyzing the intricate relationships between image histograms and the processes of contrast enhancement and white balancing, introduced a generalized equalization model that integrates these tasks seamlessly within a convex programming framework. Our model provides flexibility through parameter configurations, allowing for the accomplishment of diverse enhancement goals tailored to specific applications. By defining histogram transform properties such as contrast gain and nonlinearity, optimized model parameters to achieve optimal enhancement results for various scenarios. Moreover, derived an optimal image enhancement algorithm that effectively balances contrast enhancement and white balancing, striking a trade-off between improving contrast and minimizing tonal distortion. Through both subjective and objective experimental evaluations, the effectiveness of our proposed algorithm in tasks such as image enhancement, white balancing, and tone correction were demonstrated. Additionally, the computational complexity of the method was analyzed, showcasing its practical feasibility for real-world applications. Our Convex Programming Approach presents a versatile and efficient solution for unified image enhancement and white balancing, offering researchers and practitioners a valuable tool to improve image quality across a range of applications and domains.

REFERENCES

1. A. R. Rivera, B. Ryu, and O. Chae, (2012), Content-aware dark image enhancement through channel division, IEEE Trans. Image Process., vol. 21, no. 9, pp. 3967–3980, 2012.
2. Guo, X., Li, Y., & Ling, H. (2016). LIME: Low-light image enhancement via illumination map estimation. IEEE Transactions on image processing, 26(2), 982-993.

3. Ragan-Kelley, J., Barnes, C., Adams, A., Paris, S., Durand, F., & Amarasinghe, S. (2013). Halide: a language and compiler for optimizing parallelism, locality, and recomputation in image processing pipelines. Acm Sigplan Notices, 48(6), 519-530.
4. Reza Ghabousian and Nooshin Allahbakhshi, (2015), Survey of Contrast Enhancement Techniques based on Histogram Equalization," Int. J. Rev. Life Sci., vol. 5, no. 8, pp. 901–908, 2015.
5. R. C. Gonzalez and R. E. Woods, (2010), Digital Image Processing, Third. Upper Saddle River, NJ, USA: Prentice Hall, 2010.
6. Schindelin, J., Rueden, C. T., Hiner, M. C., & Eliceiri, K. W. (2015). The ImageJ ecosystem: An open platform for biomedical image analysis. Molecular reproduction and development, 82(7-8), 518-529.
7. Seetharaman K, Jeyakarthic M. (2013). Color Image Retrieval Based on Multivariate Parametric Tests and Measures of Divergence. International Conference on Emerging Trends in Engineering and Technology (ICETET'2013) , 22-28.
8. Seetharaman, K. and Jeyakarthic, M., (2014 a). Statistical distributional approach for scale and rotation invariant color image retrieval using multivariate parametric tests and orthogonality condition. Journal of Visual Communication and Image Representation, 25(5), pp.727-739.
9. Seetharaman K, Jeyakarthic M. (2014 b). Color Image Retrieval Based on Non-parametric Statistical Tests of Hypotheses. International Journal of Emerging Technology and Advanced Engineering, 4(08), 750-756.
10. Van der Walt S, Schönberger JL, Nunez-Iglesias J, Boulogne F, Warner JD, Yager N, Gouillart E, Yu T;(2014), scikit-image contributors. scikit-image: image processing in Python. PeerJ. 2014 Jun 19;2: e453. doi: 10.7717/peerj.453.
11. Wang, S., Zheng, J., Hu, H. M., & Li, B. (2013). Naturalness preserved enhancement algorithm for non-uniform illumination images. IEEE transactions on image processing, 22(9), 3538-3548.
12. W. A. Mustafa, H. Yazid, and S. Yaacob, (2014), Illumination Normalization of Non-Uniform Images Based on Double Mean Filtering, in 4th IEEE International Conference on Control Systems, Computing and Engineering, 2014, pp. 366–371.
13. W. A. Mustafa and H. Yazid, (2016), Illumination and Contrast Correction Strategy using Bilateral Filtering and Binarization Comparison, J. Telecommun. Electron. Comput. Eng., vol. 8, no. 1, pp. 67–73, 2016.
14. Xue, W., Zhang, L., Mou, X., & Bovik, A. C. (2013). Gradient magnitude similarity deviation: A highly efficient perceptual image quality index. IEEE transactions on image processing, 23(2), 684-695.
15. Zhu, Q., Mai, J., & Shao, L. (2015). A fast single image haze removal algorithm using color attenuation prior. IEEE transactions on image processing, 24(11), 3522-3533.
16. Li, S., Kang, X., & Hu, J. (2013). Image fusion with guided filtering. IEEE Transactions on Image processing, 22(7), 2864-2875.
17. Zhang, L., Zhang, L., & Bovik, A. C. (2015). A feature-enriched completely blind image quality evaluator. IEEE Transactions on Image Processing, 24(8), 2579-2591.

18. Zhao, H., Gallo, O., Frosio, I., & Kautz, J. (2016). Loss functions for image restoration with neural networks. IEEE Transactions on computational imaging, 3(1), 47-57.