Low-light Image Enhancement with Color Space (Cielab)

Lee Kok Xiong
Institute of Computer Science and Digital Innovation, UCSI University, Cheras, 56000 Kuala Lumpur, Malaysia

Kasthuri Subaramaniam
Department of Decision Science, Faculty of Business and Economics, University of Malaya, 50603 Kuala Lumpur, Malaysia

Umm E Mariya Shah
Institute of Computer Science and Digital Innovation, UCSI University, Cheras, 56000 Kuala Lumpur, Malaysia

Abdul Samad Bin Shibghatullah
College of Computing & Informatics, Universiti Tenaga Nasional, 43000 Kajang, Selangor, Malaysia

Oras Baker
Faculty of Computing, Ravensbourne University London, SE10 0EW, United Kingdom

Email: 1002060150@ucsiuniversity.edu.my, s_kasthuri@um,edu.my, mariya@ucsiuniversity.edu my, abdul.samad@uniten.edu.my, O.alhassani@rave.ac.uk

Abstract

In this project, we implemented a color transformation from RGB to CIELAB to enhance low-light images. This transformation separates color information from brightness information, which improves contrast and overall quality. We are using a standard color conversion formula and combining it with other techniques, such as histogram equalization and neural networks, for better results. The project will have a user-friendly interface that allows users to upload and download images and compare the original and enhanced versions. The programming language used and the specific details of the implementation process are not mentioned.

Keywords: Low-light, Image Enhancement, Color Space, Cielab

1. Introduction

The history of image processing can be traced back to the 1960s [1], when research institutions began experimenting with enhancing image quality for medical imaging, video telephony, character recognition, and satellite imagery. The goal was to improve the visual impact of low-quality images and generate higher-quality images as a result [2]. Since then, numerous types of image processing have been developed, including image enhancement, restoration, encoding, and compression [3].

Nowadays, the use of digital devices such as smartphones and digital cameras has become ubiquitous 4. However, low light conditions can have a significant impact on image quality, causing images to lose colour information, contrast, and brightness [5]. To address this issue, experts have developed various methods to enhance the quality of low- light images, including histogram equalization, illumination map estimation [6], normalization flow [7], neural networks [8], and dark region-aware low-light image enhancement [9].

To further improve the effectiveness of low-light image enhancement techniques, colour space transformations have been developed to convert RGB colour space to HSI or CIELAB colour space. This project proposes the use of colour transformation from RGB to CIELAB, along with a step-by-step implementation of the transformation and enhancement process. The project also includes a simple interface for uploading low-light images and downloading the enhanced images, as well as a comparison box to show the difference between the original and enhanced images

2. Related Work

2.1. *Histogram Equalization (HE)*

In image processing, histogram equalization is a method used to enhance contrast in images by expanding the intensity range and distributing the most common intensity levels. This allows for regions with low local contrast to receive more contrast, and intensity distributions are changed by histogram equalization. It can be divided into global histogram equalization (GHE) and local histogram equalization (LHE), with LHE being more effective in improving overall contrast. However, histogram equalization may also significantly change the mean brightness of an image, which may not be desired in some cases [10].

2.2. *Illumination Map Estimation (LIME)*

The Illumination Map Estimation (LIME) method is a new approach to enhance low-light images by estimating illumination maps for each RGB color channel separately. Unlike the variational model, LIME proposes additional illumination enhancement processes that further improve the illumination conditions of the image. LIME is considered one of the most advanced works in the field of classical algorithms and builds on the Retinex-based category. However, retinex-based methods produce undesirable results such as halo aberrations, poor contrast, and excessive smoothness in the enhanced images, and certain methods over-compute during the enhancement process.

2.3. *Normalizing Flow (NF)*

A normalizing flow is a method of transforming a simple probability distribution into a more complex distribution using a set of invertible and differentiable mappings. The layers of the network must be constructed carefully to ensure that the inversion and determinant of the Jacbian matrix can be easily captured, limiting the capacity of the generative model. Modifications have been proposed to increase the expressive power of the model, such as 1 x 1 convolution, partitioning and concatenation, permutation, and affine coupling layers. Wang et al. [11] implemented this method to accurately learn local pixel correlations and global image properties by modeling the distributions over the normally exposed image. Although this method provides saturation enrichment and color distortion reductions, it still leads to unnatural image colors [15].

2.4. *Neural Network (CNN)*

Based various image enhancement methods based on neural networks that have emerged in recent years. Inception and LLCNN use convolutional blocks in their pipelines, while ResNet uses residual connections to provide two different channels for illumination and reflection. However, these methods still result in visible visual artifacts. Mehwish et al [12] proposed a color-wise attention network method that balances color on low frequencies using a sigmoid function and preserves contrast while reducing color saturation. Lore et al [13] used LLNet, the first deep learning technique applied to low-light image enhancement, which significantly outperformed conventional techniques using a variation of the stacked-sparse denoising and contrast-enhancement autoencoder. However, a sizable amount of dataset is required for effective training.

2.5. *Dark Region-Aware Low-light Enhancement (DALE)*

The method uses visual attention and enrichment networks to improve images with low light. The attention network creates an attention map to detect dark areas, and the enrichment network enriches the image with low light [14]. The method has been successfully implemented in many images, but requires a large dataset for training.

3. Method

3.1. *Accuracy of numerical integration*

The CIELAB color space is a widely used color model that is designed to be more perceptually uniform than RGB. It separates color information into three components: L for lightness, A for the red-green axis, and B for the blue-yellow axis.

The formula provided in this paper is a way to enhance low-light images by adjusting the lightness component (L) while preserving the chroma and hue information in the image. The steps are as below:

The chroma of the image is calculated by taking the square root of the sum of the squares of the A and B components. This represents the intensity of the color in the image.

$$\text{Chroma} = \text{square root}\ (A*A + B*B) \tag{1}$$

The hue of the image is calculated by taking the arctangent of the B component divided by the A component. This represents the angle of the color in the red-green-blue color space.

$$\text{Hue} = \tan\text{-}1\ (B/A) \tag{2}$$

The overall intensity of the image is calculated by taking the average of the R, G, and B components.

$$I = (R+G+B)/3 \tag{3}$$

An alpha value is calculated based on the intensity of the image, which is used to scale the lightness component later.

$$\text{Alpha} = (255 - I)/255 \tag{4}$$

The new lightness value is calculated by adding 1 to the alpha value and multiplying it by the old lightness value. This increases the brightness of the image.

$$\text{newL} = (\text{Alpha} + 1) \text{ x oldL} \tag{5}$$

The ratio of the new lightness value to the old lightness value is calculated.

$$\text{ratio} = \text{newL}/\text{oldL} \quad (6)$$

The new chroma value is calculated by multiplying the ratio by the old chroma value. This preserves the intensity of the color in the image.

$$\text{new chroma} = \text{ratio x Chroma} \quad (7)$$

The new A value is calculated by multiplying the new chroma value by the cosine of the hue angle. This adjusts the red-green axis of the image.

$$\text{newA} = \text{new chroma x cos(Hue)} \quad (8)$$

The new B value is calculated by multiplying the new chroma value by the sine of the hue angle. This adjusts the blue-yellow axis of the image.

$$\text{newB} = \text{new chroma x sin(Hue)} \quad (9)$$

Finally, combine newL, newA and newB together then convert it back to RGB color space. By using this formula, the brightness of the image will improve and it will become clearer while maintaining the color of the image.

3.2. *System Interface*

The interface design of the LLIE system should be simple and consistent to avoid users wasting time learning how to use the system repeatedly. Therefore, the system's design was based on research of similar interfaces with features such as image upload, conversion, comparison, and download. The LLIE system uses Tkinter to build its interface, which is a simple and efficient GUI toolkit for Python.

4. Result

After applying the colour space method Fig. 1, Fig. 2, and Fig. 3 are the result of the low-light image enhancement system together with the interface used to compare the original image with the enhanced image.

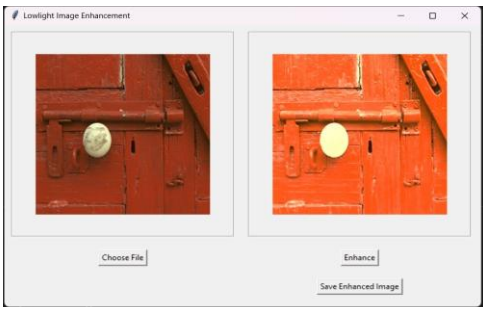


Fig. 1. Door Lock Images

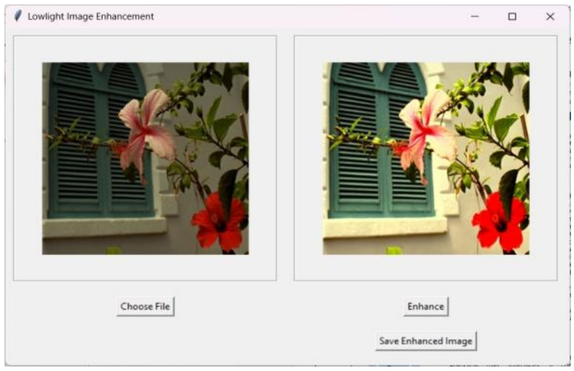


Fig. 2. Flower Images

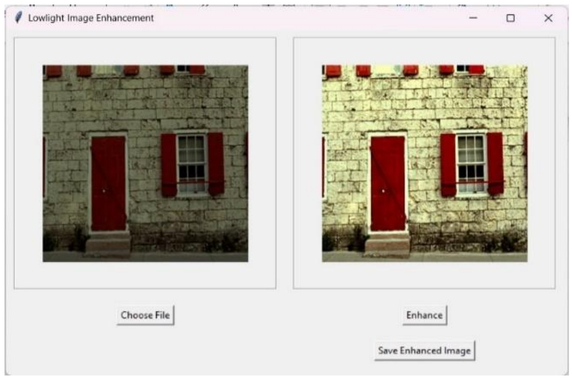


Fig. 3. Wall Images

5. Conclusion

The proposed application aims to improve the overall brightness of the image. However, the proposed application is bound and limited to the certain images and as such, further research will have to be conducted in order to expand the array of viable range of images.

In the conclusion, the result in increasing the brightness of the image helps the user to observe the object in the image clearer with the improvement of the colour but there are limitations that will need to be improved in the future work.

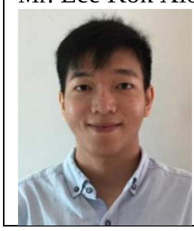
References

1. Pratt, W. K. (2007). Digital image processing: PIKS inside. John Wiley & Sons.
2. Wang, L., Zhao, L., Zhong, T., & Wu, C. (2024). Low-light image enhancement using generative adversarial networks. Scientific Reports, 14(1), 18489.
3. Feng, Y., Hou, S., Lin, H., Zhu, Y., Wu, P., Dong, W., ... & Zhang, Y. (2024). Difflight: integrating content and detail for low-light image enhancement. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 6143-6152).
4. Statista. (2022). Number of mobile phone users worldwide from 2019 to 2026 (in billions).
5. Gonzalez, R. C., & Woods, R. E. (2018). Digital image processing. Pearson Education India.

6. Guo, X., Li, Y., Ling, H., & Wu, J. (2017). LIME: Low-light image enhancement via illumination map estimation. IEEE Transactions on Image Processing, 26(2), 982-993.
7. Chen, C., Chen, Q., Xu, J., & Koltun, V. (2018). Learning to see in the dark. In Proceedings of IEEE conference on computer vision and pattern recognition (pp. 3291-3300).
8. Li, C., Ren, W., Fu, D., Tao, D., & Feng, D. (2018). LLNet: A deep autoencoder approach to natural low- light image enhancement. IEEE Transactions on Image Processing, 27(6), 2608-2622.
9. Chen, Z., Yang, J., Li, F., & Feng, Z. (2023). Real-Time Low-Light Image Enhancement Method for Train Driving Scene Based on Improved Zero-DCE. In International Conference on Electrical and Information Technologies for Rail Transportation (pp. 9-18). Singapore: Springer Nature Singapore.
10. Ismael, A. N. (2022). A comparative Study of Image Enhancement Techniques for Natural Images. J. Al-Qadisiyah Comput. Sci. Math, 14(4), 53-65.
11. Wang, Y., Wan, R., Yang, W., Li, H., Chau, L. P., & Kot, A. (2022). Low-light image enhancement with normalizing flow. In Proceedings of the AAAI conference on artificial intelligence (Vol. 36, No. 3, pp. 2604-2612).
12. Atoum, Y., Ye, M., Ren, L., Tai, Y., & Liu, X. (2020). Color-wise attention network for low-light image enhancement. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (pp. 506-507).
13. Lore, K. G., Akintayo, A., & Sarkar, S. (2017). LLNet: A deep autoencoder approach to natural low-light image enhancement. Pattern Recognition, 61, 650-662.
14. Yu, X., Bo, L., & Xin, C. (2022). Low light combining multiscale deep learning networks and image enhancement algorithm. 2(4), 0215-0232.
15. Tan Wan Yin, Kasthuri Subaramaniam, Abdul Samad Bin Shibghatullah and Nur Farraliza Mansor, 2022. Enhancement of Low-Light Image using Homomorphic Filtering, Unsharp Masking, and Gamma Correction. International Journal of Advanced Computer Science and Applications (IJACSA), Vol. 13, No. 9, pp. 53-60.

Authors Introduction

Mr. Lee Kok Xiong



He is currently an undergraduate student, pursuing his study in Bachelor of Science (Hons) in Computing from Institute of Computer Science and Digital Innovation (ICSDI) at UCSI University, Malaysia.

Dr. Kasthuri Subaramaniam

She received her Bachelor's and Master's degrees in Computer Science from University of Malaya. She earned her Ph.D. in Informatics from Malaysia University of Science & Technology. Her research interests include human-computer interaction, human personality types, augmented reality, e-learning, mobile commerce and e-commerce.

Dr. Umm e Mariya Shah

She received the Ph.D. degree in Computer Science from Universiti Malaya, Malaysia and the MS degree in Computer Science from COMSATS University, Islamabad, Pakistan and the BS degree in Computer Science from Pir Mehr Ali Shah Arid Agriculture University, Rawalpindi, Pakistan. Her research areas include usability engineering, human-computer interaction, and healthcare (ICT, interdisciplinary).

Dr. Abdul Samad Bin Shibghatullah

He received his Bachelor's degree in Accounting from Universiti Kebangsaan Malaysia, M.Sc. degree in Computer Science from Universiti Teknologi Malaysia and Ph.D. in Computer Science from Brunel University, UK. He is currently an Associate Professor at the College of Computing & Informatics (CCI), Universiti Tenaga Nasional, Kajang, Malaysia.

Dr. Oras Baker

He is an Associate Professor and Head of Masters in Cyber Security and Cyber Security Management at Ravensbourne University London, UK. With 25 years of distinguished experience spanning academia, research, and industry, he specialises in Artificial Intelligence, Software Engineering, Cyber Security, Data Mining, and Machine Learning.