Detecting Shadows in Computer Vision: A MATLAB-Based Approach

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Chronicle

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Abstract

The abstract outlines a novel MATLAB-based technique for enhancing shadow detection accuracy in computer vision applications. This MATLAB-based method uses thresholding and color analysis to improve the accuracy of shadow identification. Luminance (L*) is distinguished from chromaticity (a* and b*) in digital photographs by converting them into the Lab color space. This makes it easier to identify possible shadowed areas. The luminance channel's thresholding makes it possible to distinguish between regions that are well-lit and those that are shadowed. The computation of chromaticity distance also helps in detecting modest color changes that are suggestive of shadows. The culmination of the suggested technique is the creation of a binary shadow mask, which isolates the image's shaded regions. The research addresses limitations of existing approaches by maintaining robustness in diverse lighting conditions and complex scenarios, thereby enhancing image comprehension and the precision of shadow detection. The proposed technique holds promise for improving object recognition and scene analysis in computer vision applications, offering a robust and reliable solution for identifying and isolating shadows in digital images.

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INTRODUCTION

In this paper, we introduce a MATLAB-based technique for shadow recognition in digital images with the goal of differentiating between shadow regions and other dark areas Kim et al. (2018). Shadows can distort item appearances and complicate segmentation methods, therefore accurate shadow detection is essential for many computer vision applications, including object recognition and scene analysis Feng et al. (2022). Because of fluctuations in lighting conditions and complicated sceneries, traditional approaches for shadow identification frequently fail to distinguish effectively between shadows and other dark regions. We use the Lab color space Tanoglidis et al. (2021), which divides color information into three parts: chromaticity (a* and b*), which represents color information, and luminance (L*), which represents picture intensity, to get around these problems. Since shadows only slightly change color, they mostly affect the luminance component, making this distinction crucial for shadow detection. Our method improves the accuracy of shadow recognition by successfully separating shaded regions from non-shadowed areas by examining the luminance channel irrespective of chromaticity. Furthermore, the Lab color space provides a uniform color representation that is perceptually accurate, which makes it an excellent choice for evaluating color variations under a variety of lighting circumstances Wang et al. (2020). Thus, our

methodology tackles the shortcomings of previous approaches and offers a more robust and dependable solution for precise shadow identification in digital photographs by utilizing the benefits of the Lab color space.

LITERATURE REVIEW

The effects of shadows on object tracking and recognition have historically been a source of difficulty for the shadow detection field in security camera systems. This is often because color-based and gradient-based algorithms are prone to variations in illumination and backdrop brightness Vasu et al. (2023), Abro et al. (2021). Recent research offers creative solutions incorporating deep learning techniques, especially Convolutional Neural Networks (CNNs), for shadow detection in order to get around these issues Luo et al. (2020). In order to enable more accurate and reliable shadow identification across a variety of lighting situations and complicated scenarios, CNN-based techniques have demonstrated encouraging results in learning complex patterns and features from huge datasets. Furthermore, the ability to detect shadows has improved due to recent developments in color analysis and feature extraction techniques. For instance, using Lab color space transformation has improved the separation of chromaticity and brightness components, making it easier to identify shaded areas with greater accuracy, Fan et al. (2020). Furthermore, techniques that use chromaticity distance calculation have increased algorithms' accuracy by capturing minute fluctuations that are indicative of shadows. Moreover, new directions for shadow detection studies have been made possible by the development of multispectral and hyperspectral imaging technology. Richer spectral information provided by these imaging modalities enables more thorough study of shadow properties and improved distinction between shadows and other picture aspects, Cun et al. (2020). In addition, there has been an increase in the integration of shadow detection into more comprehensive computer vision frameworks, like semantic segmentation and object detection. Researchers want to improve item detection in shaded contexts and overall scene understanding by integrating shadow awareness into higher-level vision tasks [9]. Overall, increasingly complex approaches that make use of deep learning, sophisticated color analysis methods, and multimodal imaging modalities have been adopted recently in shadow detection research, Inoue et al. (2020), Abro (2021). These developments have the potential to improve computer vision systems' practical applications and solve long-standing issues with shadow detection.

PROPOSED APPROACH

Lab Color Space
The initial step of our technique involves the conversion of input digital images into the Lab color space. The Lab color space is a three-component color model, consisting of the luminance component (L*), represents image intensity, and the chromaticity components (a* and b*), which represent color information. The choice of the Lab color space is pivotal due to its unique ability to separate luminance from chromaticity in Figure 2. The separation of these components is especially significant in the context of shadow detection. Shadows predominantly influence the luminance component of an image, causing variations in brightness without significantly altering color. By isolating luminance

from chromaticity, we create a solid foundation for distinguishing shadowed regions from non-shadowed areas.

Luminance and Chromaticity Extraction

Once the images have been transformed into the Lab color space, the next step is to extract the luminance (L*) and chromaticity (a* and b*) channels. The luminance channel is of particular importance in the context of shadow detection. It captures information about the intensity or brightness of the image, making it a crucial component for identifying shadows. In contrast, the chromaticity channels, a* and b*, provide information about the color characteristics within the image. Extracting these channels allows us to analyze color variations, which is essential for distinguishing between shadowed areas and regions with inherent color differences.

Thresholding

Setting appropriate thresholds is a critical aspect of our shadow detection method. These thresholds are determined through an analysis of the luminance channel. Thresholding the luminance channel helps identify regions in the image where shadow is likely to be present. This step is essential for distinguishing shadowed areas from well-illuminated regions, as it effectively separates dark regions that are caused by shadows from those that may simply be naturally dark or differently lit. The choice of threshold values is a crucial parameter, as it influences the sensitivity and specificity of the shadow detection process.
On high intensity lighting higher thresholding value should be & low intensity lighting needs low thresholding value but sensitivity should be adjusted without noise & artifacts likewise for high intensity lighting sensitivity should be increase. These thresholds should be fine-tuned to strike a balance between correctly identifying shadow regions while minimizing false positives.

Chromaticity Distance Calculation

To further refine the shadow detection process, we employ the calculation of chromaticity distances in the chromaticity channels (a* and b*). Chromatic distance measures variations in color within these channels and is particularly useful for identifying subtle color differences indicative of shadows. This metric aids in distinguishing between color variations caused by the presence of shadows and those arising from inherent object properties or changes in lighting. By calculating chromaticity distances, our method can effectively identify shadows even when they exhibit subtle color variations, contributing to the precision and reliability of the shadow detection process.

Binary Shadow Mask

The culmination of our technique is the generation of a binary shadow mask. This mask serves as the final output, highlighting the shadowed areas within the image. It is created by combining the information obtained from luminance thresholding and chromaticity distance calculation, Hu et al. (2019). The binary shadow mask effectively segregates the shadowed regions from the rest of the scene, producing a clear distinction between areas affected by shadows and those that are well-illuminated. This mask can be used in subsequent computer vision tasks, such as object recognition or scene analysis, to improve the accuracy of these processes by considering the presence of shadows.
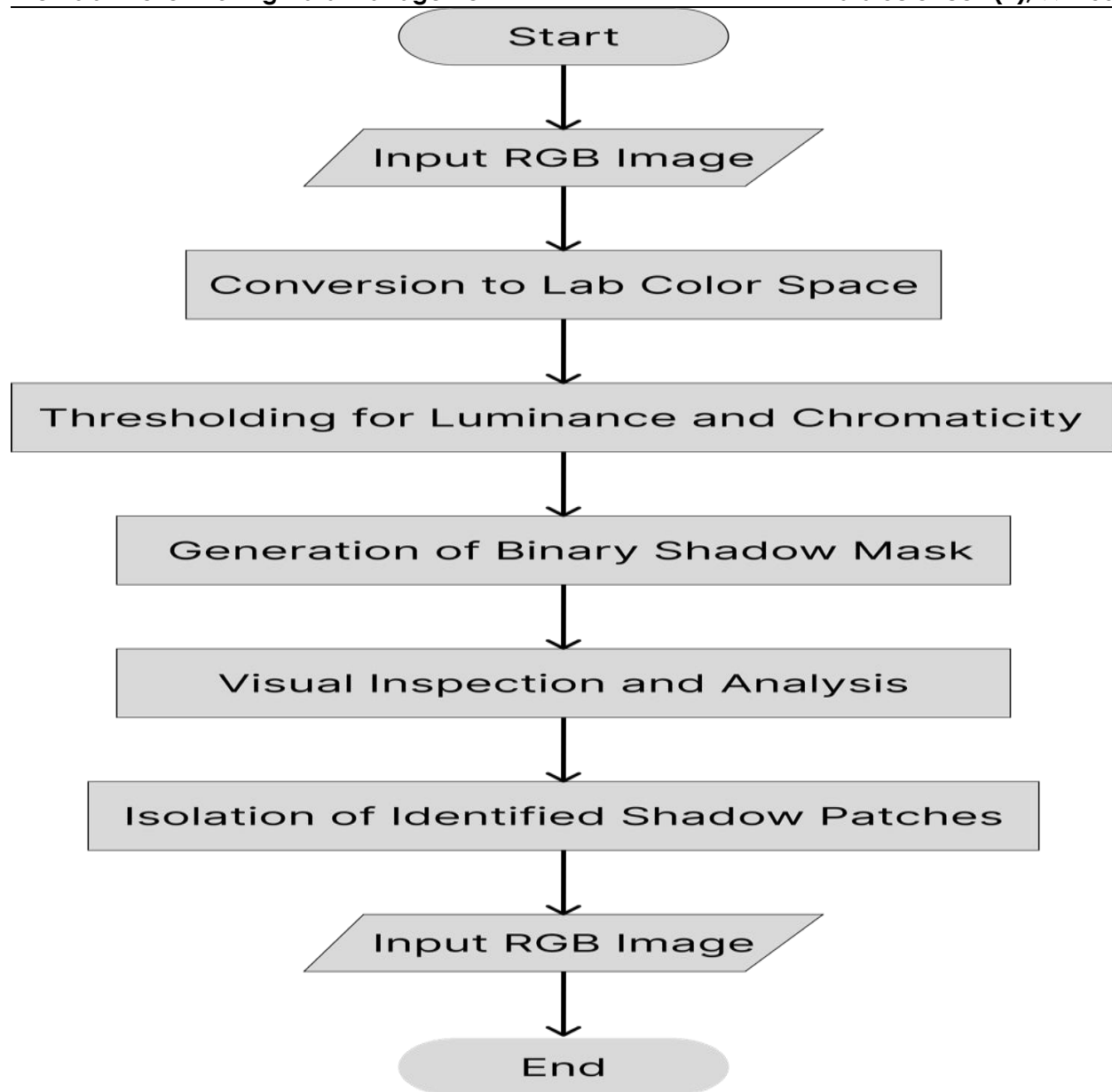
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Figure 5.
Flow Chart

RESULT & DISCUSSION

To find potential shadow regions, the given code analyzes an RGB image in Lab color space. White pixels represent potentially shaded areas in a binary shadow mask created by applying thresholds to luminescence and chromaticity. In order to facilitate visual inspection, the shadow mask and the original image are shown side by side. The code also shows how to isolate and show only the identified shadow patches from the original image. This method makes use of color differences to recognize shadows and provides a customized shadow detection solution with adjustable sensitivity, allowing for additional analysis or focused processing of shaded areas

METHODOLOGY

The offered code uses a rule-based methodology including thresholding and color space transformation (Lab) to identify shadows. To find potential shadow locations, it primarily uses chromaticity and luminance. On the other hand, a CNN-Based Shadow Detection method requires training a convolutional neural network, a type of deep learning model, on a large set of labeled shadow and non-shadow photos. The CNN becomes more data-driven and may be able to capture complicated shadow variations as it learns sophisticated patterns and features from the data to create predictions about shadows.

Data Dependency

The provided code operates on a single image using predetermined thresholds; thus, it doesn't require a sizable training dataset. It is a rule-based approach and does not incorporate considerable data learning. Data is a key component of CNN-Based Shadow Detection. A sizable collection of labeled shadow and non-shadow photos is necessary for model training. Although it necessitates a lot of data collecting and annotation work, this data-driven approach may adapt to different real-world events better

Customization

The provided code offers some customization to enable for adaptation to various images and lighting situations by allowing users to choose the threshold values for luminance and chromaticity but in the architecture design and hyperparameter tuning involved in CNN based systems are often quite thorough, but they may not offer the same amount of instant customization as the rule-based approach.

Computational Complexity

The offered code may be swiftly executed, is computationally lightweight, and is appropriate for real-time applications but CNN-based methods need a lot of computes during both training and inference, their usage in real-time scenarios without powerful hardware may be constrained.

Image Dataset Sensitivity

The sensitivity of our shadow detection technique to differences in picture datasets depends on various aspects, including scene complexity, image quality, diversity of datasets, and forms of shadows. Robustness is improved by a broad dataset; nevertheless, sensitivity may be introduced by poor quality photos or complex scenarios. Preprocessing procedures, dataset augmentation, and specific methodologies can be used to lessen these impacts. Continuous assessment using a variety of datasets is necessary to improve the method's resilience and sensitivity over time.

Figure 1. Output of proposed method Displays both the algorithm-generated shadow mask (b) and the original input image (a). Based on the applied thresholds and color analysis, the shadow mask identifies regions of the image as shadows. Converting shadow mask into Binary shadow mask (c) & then mask multiplication

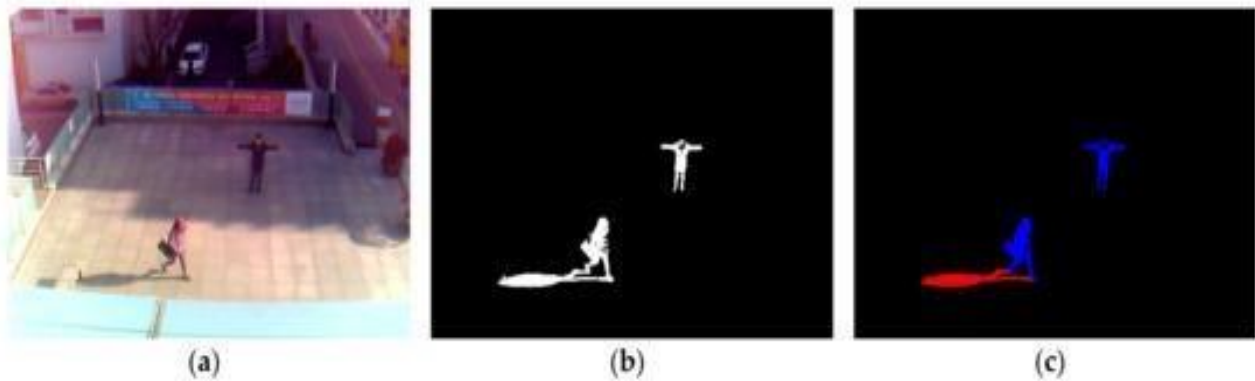**Figure 1.**
Output of proposed method

Figure 2.
Output of referenced methodology

Figure 3.
Output of Shadow Mask method

Improvement

The shadow detection code offered is a rule-based method that depends on thresholding and color space transformation to identify shadows. It is quick and easy to use, making it suited for real-time or resource-constrained applications. It lacks the adaptability and data-driven powers of Convolutional Neural Network (CNN)-Based Shadow Detection but does allow for some customization through threshold modifications. On the other hand, CNN-Based Shadow Detection is a data-driven method that uses deep learning to handle various complicated shadow scenarios with improved accuracy, however it necessitates a significant amount of processing power and training data. The decision between them relies on the requirements of the particular application; the given code excels in readability and simplicity, whilst CNN-based approaches provide higher accuracy and adaptability in difficult shadow detection scenarios. Given code is less iterative as compare to Image Shadow Detection and Removal Based on Region Matching of Intelligent Computing in Figure 4.
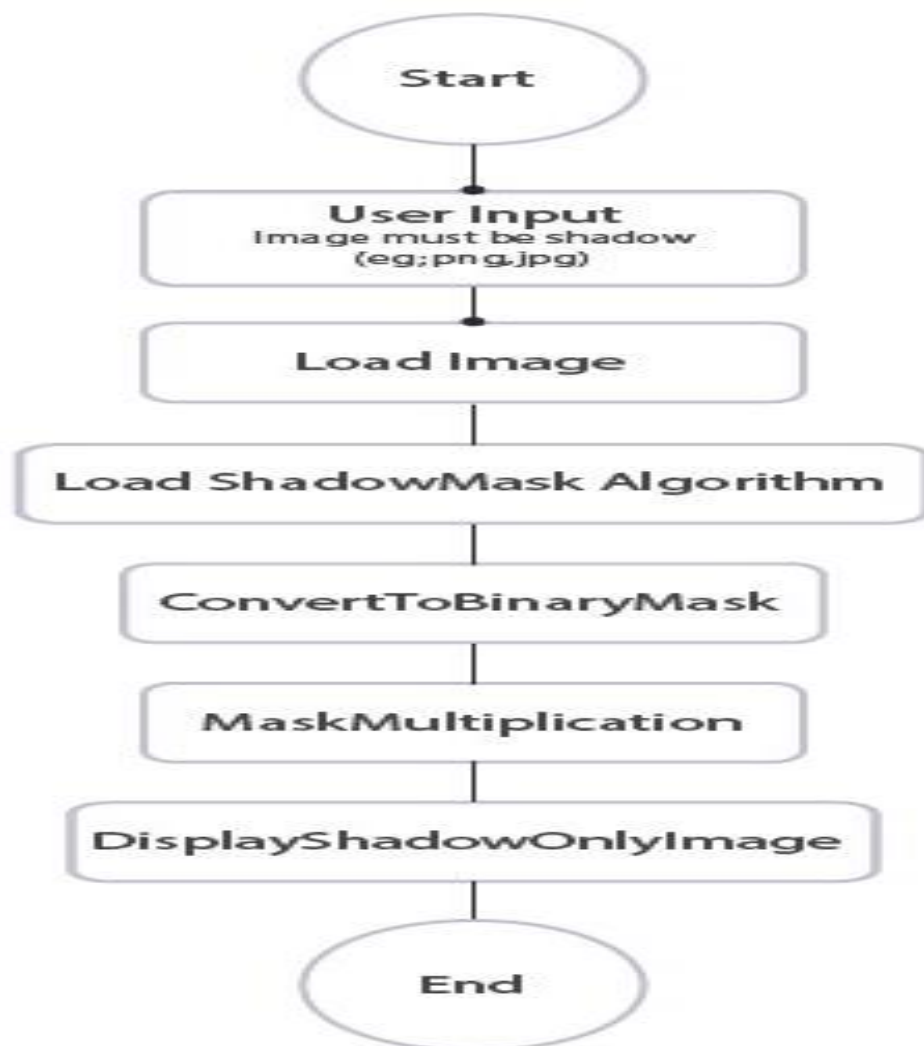

Figure 4.
Framework Diagram

According to Table 1, outcomes, the number of rows for each mask corresponds to how successfully the algorithm identified shadowy areas. For instance, Mask 2's precision is 0.196, recall is 0.468, and F1-Score is 0.276, indicating that this mask managed to identify shadows with a considerable level of recall but just a little bit of precision. Mask 2 and Mask 17, which have relatively high F1-Scores. On the other hand, masks with accuracy and recall values of zero, such as Mask 5 and Mask 10, result in undefined F1Scores, indicating that these instances failed to accurately identify any shadows. Masks with higher F1-Scores balance precision and recall better, whereas masks with lower scores show trade-offs between these two criteria, Abro et al. (2020). Some masks provide precision, recall, and F1-Score values that are either very low or zero, indicating poor shadow detection performance. We can improve shadow detection performance by setting different threshold values.

Table 1.
Precision Matrix

Data Set	Precision	Recall	F1-Score
1	0.058502692	0.044290148	0.050413879
2	0.195512031	0.468490185	0.275889042
3	0.128713612	0.290256168	0.178341836
4	0.333107633	0.304213398	0.318005526
5	0	0	NAN
6	0.189730745	0.08396453	0.116411603
7	0.816128598	0.159007602	0.266159028
8	0.633936615	0.097362496	0.168800017
9	0.816128598	0.159007602	0.266159028
10	0	0	NAN
11	0.02556391	0.140206186	0.043243243
12	0.665551839	0.007998071	0.015806195
13	0.133784341	0.343357543	0.192545925
14	0.061971709	0.227178588	0.097379428
15	0	0	NAN
16	0.271167883	0.096418375	0.142255409
17	0.254549179	0.651065316	0.366001522
18	0.002017694	0.003471295	0.002552022
19	0	0	NAN
20	0.152173913	0.002913935	0.00571837

COMPARISON

To deepen the comparison, we will explain why a rule-based approach with thresholding is preferred over CNN-based methods, and vice versa. Rules-based approaches are easy to understand, efficient in terms of processing, and appropriate for situations with little or no labeled data as well as real-time applications. They provide the option to manually modify thresholds to account for changes in illumination and image attributes. CNN-based techniques, on the other hand, are highly adaptive and perform well in a variety of shadow settings since they are excellent at directly learning intricate patterns and features from data. Nevertheless, in contrast to rule-based techniques, they are more interpretable and demand a substantial amount of computer power. Based on particular application requirements and limits, a nuanced comparison taking into account

elements like performance, interpretability, and computational complexity will direct the choices.

CONCLUSION

Our methodology utilizing color analysis, thresholding, and feature extraction techniques, our research substantially advances the field of shadow detection. The work we have done is noteworthy since it has resulted in a strong algorithm for detecting shadows in digital photos and effectively separating them from well-lit areas. Our method shows promising results in reliably recognizing shadows across various datasets by utilizing the Lab color space and implementing thresholding strategies. The metrics are strongly influenced by the threshold for translating algorithm predictions into binary masks (shadow vs. non-shadow). The threshold could be adjusted for better performance overall. According to the analysis, the algorithm can be strengthened to increase its capacity for shadow identification. Its performance may be improved using approaches like feature engineering, algorithm improvement, or the use of more sophisticated machine learning methods. In comparison to Image Shadow Detection and Removal Based on Region Matching of Intelligent Computing given algorithm can be optimal solution. The algorithm's performance can be improved. An improved and more dependable system for detecting shadows can be created through this iterative process of research and improvement in detecting required thresholding value.

DECLARATIONS

Availability of data and material: In the approach, the data sources for the variables are stated.
Authors' contributions: Each author participated equally to the creation of this work.
Conflicts of Interests: The authors declare no conflict of interest.
Consent to Participate: Yes
Consent for publication and Ethical approval: Because this study does not include human or animal data, ethical approval is not required for publication. All authors have given their consent.

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