Image Shadow detection and Removal using relighting technique

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Abstract—Shadow detection and removal are important tasks when dealing with outdoor images, and they help to enhance the performance parameters like accuracy and reliability of many machine vision applications. Shadows are generated by the absence of light. Moreover, shadow-free images are of great interest for image editing, computational photography, and augmented reality, and the first crucial step is shadow detection. This paper uses the technique of entropy minimization to find an invariant image from an RGB image with shadows. An invariant image is free of lighting conditions, and shading can be removed to some extent. Since they capture the intrinsic reflectivity of the objects in the image regardless of illumination, these invariant images are also referred to as inherent or intrinsic images. This paper presents shadow detection by calculating invariant images and subsequent removal using the relighting technique. The advantage of the demonstrated algorithm is its ability to detect and remove shadows while consuming low computational and time resources.

Keywords—Entropy minimization, invariant image, relighting techniques, shading, shadow detection, shadow removal.

I. INTRODUCTION

Images of natural scenes typically include shadows, which convey valuable information about the scene, such as the shape of objects, lighting conditions, camera settings, and scene geometry. However, shadows can also pose challenges for various computer vision tasks, ranging from object detection to tracking and image segmentation. Automatic detection and removal of shadows can offer numerous advantages to applications such as image editing, computational photography, and augmented reality. This can streamline the process of image manipulation and enhance the quality of resulting images. Therefore, the first critical step in achieving shadow-free images is to develop an effective shadow detection algorithm.

This paper presents an improvised version of the existing technique proposed by Graham D. Finlayson, Mark S. Drew, and Cheng Lu to identify shadows in images where an illumination-invariant image is created by projecting the band-ratio chromaticity colour coordinates in a specific direction and obtaining the logarithm of those coordinates. The input colour data is an array of 3-dimensional red, green, and blue components, and in essence, the chromaticity is 2D colour. Projecting in a 2-space direction generates a 1D, grayscale image. An illumination-invariant grayscale image is produced, independent of the lighting at each pixel as long as the direction is appropriately selected. The invariant's ingenuity lies in its independent generation for each pixel, requiring no global image processing.

One way to project an image is by using a direction that is perpendicular to the direction of the changing light source in a simplified model. This eliminates the effect of lighting and reduces the visibility of shadows in the resulting image.

In computer vision and object recognition, shadows can often interfere with the accurate detection of objects in an image. Removing shadows from images can help improve the accuracy of object recognition algorithms. Shadows in surveillance videos can obscure important details, making it difficult to identify individuals or objects. Removing shadows can help improve the quality of surveillance footage, and thereby enhance security. Augmented reality: In augmented reality applications, shadows can interfere with the accuracy of virtual objects overlaid on real-world scenes. Removing shadows can help improve the realism and accuracy of augmented reality applications. Autonomous vehicles: Shadows can be particularly problematic for autonomous vehicles, as they can cause misinterpretations of the environment and lead to errors in navigation. Removing shadows from camera feeds can help improve the reliability and safety of autonomous vehicles. Image editing and enhancement: Shadow removal can also be used for image editing and enhancement, particularly for photographs taken in difficult lighting conditions. Removing shadows can help improve the overall quality and appearance of an image.

Numerous tools and software automatically detect and eliminate shadows in digital images and videos. These include Adobe Photoshop, OpenCV, MATLAB, and many others. However, it's important to note that shadow removal can be a challenging task, especially in complex scenes with multiple light sources and objects of different shapes and colours. It may require a combination of different techniques and manual adjustments to achieve the desired results.

II. RELATED WORK

Various methodologies employed for the detection and removal of shadows using processes and techniques like texture analysis, colour information, Gaussian mixture model (GMM), and deterministic non-model-based approach were discussed. A survey of several different algorithms and methods of detecting and removing shadows with a comparative study has been done and different methods perform better in different settings [1]. Usually, the challenge of detecting shadows present in single images of natural scenes is addressed. In contrast to traditional methods that employ pixel properties or edge information, a region-based approach is also done in addition to considering distinct regions individually, comparative illumination characteristics of segmented regions from their appearances are predicted and a pairwise classification based on such information is done. A graph of segments is constructed using the classification results. Image matting is then employed for refining the resulting image, and each pixel is relighted by the lighting model, hence recovering the original image. In addition, a new dataset that includes ground truth images without shadows has been created, which offers a quantitative framework for evaluating shadow removal [2]. This method is complex and requires high computational time.

One approach to automatically detect and remove shadows in a single image is through the use of Machine Learning and Neural Network techniques. This involves training a model using Convolutional Deep Neural Networks (ConvNets) to learn relevant features for shadow detection, followed by the use of a shadow mask. The Bayesian formulation can be employed for automatic shadow removal, and this method has been shown to work well for both umbra and penumbra shadows [3]. A framework has been developed for the automatic detection and removal of shadows in real-world scenes, which uses multiple ConvNets to learn superpixel-level features along dominant boundaries in a supervised manner. Based on the learned features, posterior prediction is done. These predictions are then fed to a conditional random field model that produces a smooth shadow mask. These are then used for extracting shadow matte by applying Bayesian formulation and subsequently, shadows are removed. The Bayesian formulation has been derived from a novel model used to model the process of accurate generation of shadows in penumbra and umbra regions [4]. Another method for shadow detection for real-time moving vehicle and traffic sequences works on two aspects; (a) it performs an image-line analysis. (b) Extracts the intensity of illumination and special relationship among pixels [5]. The problem is due to the labelling of image regions, where every region is associated with a group of super pixels. The model is trained using the Least-Squares Support Vector Machine (LSSVM) to predict each region's label, this results in the distinction between shadow and non-shadow regions. For each region of the shadow area, a trained classifier is used to identify a neighbouring region of the same material that is lit. Extensive experiments were performed to evaluate the proposed shadow detection method and leave-one-out kernel optimization. To get the final results complex methods followed [6]. In another method, a database of ten thousand five hundred images containing shadows is compiled, where each image contains labels of ground-truth mask for enabling functionality in complex scenarios, and the model of the shadow detection network with detail enhancement is aimed at harvesting shadow details. By analyzing the results, this method cannot achieve high performance on new datasets, different from what has been achieved in the existing datasets [7]. An end-to-end framework called Distraction-aware Shadow Detection Network (DSDNet) explicitly learns and integrates the semantics of visual distraction regions because existing works still struggle with ambiguous cases where the visual appearances of shadow and non-shadow regions are similar, a phenomenon known as distraction. The framework consists of a unique Distraction-aware Shadow (DS) module that can be used alone and is differentiated. It anticipates false positives and negatives, minimising distractions and making discriminative features easy to spot. This leads to increased operational efficiency. Although this method can handle most challenging cases, it may fail on some weak shadow images or some images with a very dark background. [8].

Other application-based shadow detections and removal methods have been discussed in several papers which vary in processes according to the applications to which are applied. There is a significant amount of information contained in high-resolution satellite images. In such images, shadows generate challenges in the classification and obtaining the necessary information. The signals recorded in shadow areas are not strong, but they can still be retrieved. In some cases, dark vegetation is misclassified as shadow pixels, which remains an issue. In this, multiple bands are employed to generate a new index for the image. An automatic threshold identification algorithm is used to classify shadow pixels from the index of the histogram. Classified shadow pixels are then compensated by the application of the linear correlation method. The proposed approach is validated by applying two standard approaches to the same area of study [9]. Another approach to automatically detect and extract shadows in real-time moving vehicles is based on various properties acquired by the spectral, temporal, and geometric analysis of shadow, which detects the shadow region using the time and direction of the shadow. A spatial analysis method was employed to examine potential shadow areas by considering the direction of the shadow based on the time of day. Colourimetric analysis was then utilized to confirm the hypothesis of the identified region [10].

The detection of shadows and their removal from a single image Using LAB Color Space is a simple method. A method for shadow detection is selected based on the mean value of the RGB image in the A plane and the B plane of the LAB equivalent of the subject image. The shadow is removed by multiplying the shadow region by a constant. The shadow removal technique detects and corrects the shadow edge and reduces errors that occur at the shadow boundary. This method yields quick results and does not require multiple images or camera calibration. However, a potential issue with this approach is the misclassification of dark objects as shadow areas [11]. There are two other approaches, which are IOOPL and K-means clustering. The first way involves shrinking the shadow's perimeter inward and then expanding it outward to obtain the inner-outer outline Profile Lines or IOOPL. Thus, the characteristics of objects on both sides of the boundary are obtained. By comparing the inner and outer loops, color is added and shadows are removed, leading to an image without any shadows. Keeping a specific distance between each data point is the primary parameter used in the K-MEANS clustering process to categorize the data points into distinct clusters. After clustering the data points, the shadow area is computed by comparing the shadow region and the mask. The K-MEANS method yields better results as compared to the IOOPL [12].

While other methods discussed so far give the required result with few limitations one of which is being highly computational and expensive to implement another approach proposed by G.D Finlayson to improve computational time, is shadow detection using entropy minimization. Here, the 2D log-chromaticity representation of the image is formed then the entropy of the image is calculated. For shadow removal, the min-entropy direction is the appropriate projection. The objective of automated processing of unsourced imagery is to remove shadows. Results suggest that this kind of processing can eliminate shadows [13]. Another innovative technique is being considered, which utilizes the intrinsic image invariant with luminance and classical background subtraction.

Here a simplified algorithm is used which normalizes sample data and fixes bin numbers to find the image's characteristic angle. The shadow area can be determined using a region comparison method that uses KNN. The segmentation threshold can be obtained by the OTSU method which adapts to image content changes. This method is demonstrated to improve the detection rate and reduce false alarm rates through quantitative evaluations and comparisons the rate of detection is above 80% and the rate of false alarms is below 16% [14].

A machine learning technique and morphological operations are used for shadow detection and removal from images. An ESRT (enhanced streaming random tree) model is presented where the image is converted to HSV and 26 different performance parameters are considered as image measurements. Shadow and non-shadow images are taken from a dataset created in the Attribute Relation File Format. Classification efficiency is improved as compared to other state–of–the–art algorithms [15]. Comparative analysis of various shadow detection and removal techniques is presented with its pros and cons. Around 13 shadow detection techniques are discussed in this review paper. Each technique is discussed with a different analysis of the method. The final analysis showed that there is no such the best Algorithm. So the choice of the foremost algorithm is based on dataset features and Conditions like Outdoor and Indoor sequences [16].

An intelligent computing method is utilized to match materials between image regions to detect and remove image shadows by considering an image as a small sample. This approach achieves an improvement is more than 6% in comparison with other advanced shadow detection methods. The limitation of this method is that it is difficult to ensure the accuracy of region matching for complex images causing wrong constraints due to wrong matching or restoring the region to the wrong material. Another limitation is that to mean shift image segmentation algorithm causes difficulty in segmentation accurately in complex images [17].

The unsupervised methodology SUShe is purely based on colour image features. The initial extraction of the shadow region is done automatically by an Electromagnetic-Like Optimization. Super Pixel-based segmentation is utilized to extract the non-shadow region, and there are pairs of shadowed and non-shadowed regions that are nearest neighbours in terms of their colour content and are identified as parts of the same object. Histogram matching is used to illuminate the shadowed part of each pair, based on the contents of their non-shadowed counterpart. It generally has less computational complexity than the state-of-the-art algorithms for shadow removal.

SUShe can remove shadows better as compared to other state-of-the-art unsupervised shadow removal algorithms [18].

In unsupervised approaches, tactics and intrinsic image properties, such as colour and texture, are taken into account to recover the detail and luminosity of shadowed areas. [19, 20, 21, 22,]. High-quality results are typically produced by supervised methods that are mostly built on intricate deep-learning structures. [23, 24, 25, 26].

It is often difficult to achieve a detailed and boundary-smoothing shadow removal result with deep learning-based shadow removal methods. To prevent this, a filter that detects lighting and a multi-task generative adversarial network architecture is employed. Initially, the shadow is detected and the illumination-sensitive filter is applied to extract the texture information to generate a coarse image with fewer texture details. After that, an indirect shadow removal process is carried out using an illumination estimate for this coarse shadow image. Next, to accurately create a shadow boundary using the painting's picture. Finally, the texture details are recovered to obtain the final shadow removal result. An illumination-sensitive filter is presented for image decomposition and a multi-task GAN architecture. To produce a Low Error Synthetic Dataset, it also provides filters with two huge benchmarks SRD and ISTD. It lowers the inaccuracy between image pairs and increases shadow sceneries. The results of the numerous trials have demonstrated the benefits of illumination-sensitive filters and illumination estimates for shadow removal and detail retention. [27].

In this paper, an unsupervised method is used where shadow detection is done by calculating invariant images and subsequent removal using the relighting technique. The advantage of the demonstrated algorithm is the ability to detect and remove shadows while consuming low computational and time resources.

III. PROPOSED METHOD

Shadow-free images are of great utility for image editing, computational photography, and augmented reality, and the crucial first step is the detection of shadows. Illumination conditions create problems for many computer applications. Shadows present in an image have the potential to impede the functionality of segmentation, tracking, or recognition algorithms, leading to their failure. An illumination invariant of an image demonstrates great utility in a wide range of applications in both Computer Graphics as well as Computer Vision. However, calibrations are necessary for finding the invariant image, which limits the method's applicability. When less information is available about the image, an invariant image can still be generated without employing a calibration process by performing entropy minimization on the subject image. As the lighting conditions under which different images are captured vary, transforming the images from 3-three-dimensional RGB channel representation to 2-dimensional chromaticity colour space {G/R, B/R}, and taking its logarithm results in values across varying lighting conditions falling on a straight line in a 2-dimensional scatter plot. If the change of illumination amounts to movements along such a line, then projecting 2-dimensional points of chromaticity in 90 angles will generate a 1-dimensional illumination invariant image. The result is a greyscale image, independent of lighting. Therefore, an intrinsic to the subject image only portrays the inherent reflectance properties in the scene. As shadows are the result of the absence of lighting, such images have shadows removed to some extent. Figure 1 shows the block diagram of single-image shadow detection.

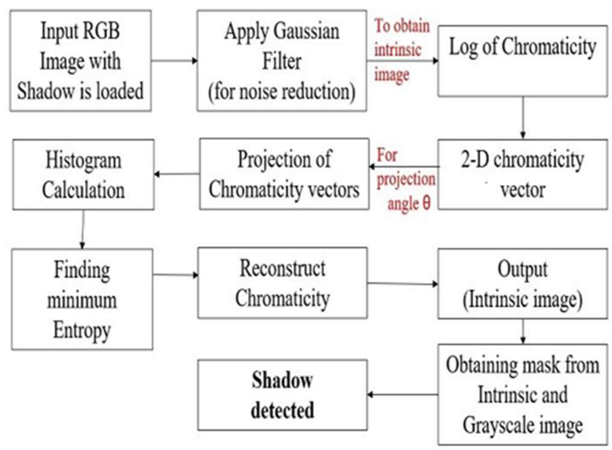

Figure 1. Block Diagram of Shadow Detection

The subject image has shading removed because it is not influenced by lighting. Because they preserve the intrinsic reflectivity of the objects in the image regardless of lighting conditions, these invariant images are also known as intrinsic images in the literature.

This paper uses the technique of Entropy Minimization to find an Invariant image from an RGB image with shadows. After uploading the image in the system, divide any two colour channels from the third channel and generate the 2-vector chromaticity (band-ratio) as shown in equation 1.

$$C\_k = R\_k/R\_p \tag{1}$$

where p is fixed to a single colour channel and k is indexed across the other two channels.

Next, since the illumination intensity component, I is constant for all three colour channels at every pixel in the original image, it can be eliminated. for example, one would utilize the blue channel as the divisor, which would result in c = {RG/RB, RR/RB}.

Taking the log of chromaticity vectors, we define the 2D chromaticity vector, in the direction in which the image exhibits minimum entropy. This minimum entropy is considered as the correct angle of projection indicating that the chromaticity values projected in that particular direction have the maximum statistical coherence. For this, simply rotate from 0◦ to 180◦ and project the log-chromaticity (2-vector) image in that direction. Then, a histogram is generated. The calculation of entropy is carried out by dividing the histogram by the sum of the count of intervals (bins) to form probabilities π, and for the occupied bins, the sum of ($-\pi \log_2 \pi$) is formed.

Once the invariant image is obtained, reconstruct chromaticity by adding bright pixels. The mask is obtained by calculating the difference between the intrinsic image and the grayscale of the subject (original image). By applying the mask on the image, we get the desired output that is Shadows are detected in the image.
Once the shadow is detected next step is to remove the shadow. Figure 2 shows the block diagram of the Single Image Shadow removal.

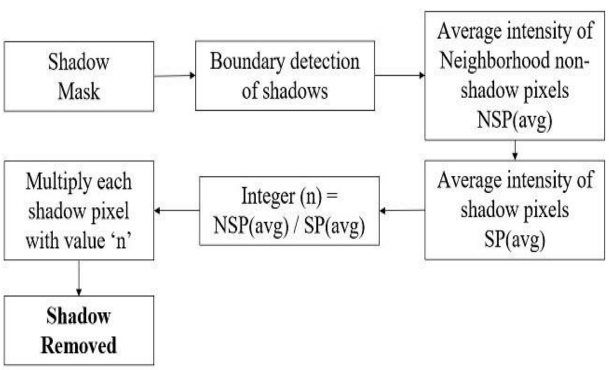

Figure 2 Block Diagram of Shadow Removal

Once the shadow is detected next step is to remove the shadow. Figure 2 shows the block diagram of the Single Image Shadow removal.

From the shadow, the mask gets connected to components that indicate shadows. Since there may be many connected components, we run a for loop to remove shadow for each connected component. Obtaining the boundary of shadows, take the summation of non-shadow pixels near the shadow edges present in the original image. Dividing the result of summation with the number of boundary point's results in the average intensity of non-shadow pixels. Taking the summation of intensities of shadow pixels and normalizing it with the number of total shadow points, the average intensity of shadow pixel is obtained

$$n = (\sum non\ shadow\ pixels)/(\sum shadow\ pixels) \quad (2)$$

After obtaining these two quantities, divide the average intensity of non-shadow pixels by the average intensity of shadow pixels as given in equation 2. The result obtained is used to multiply each shadow pixel to get an approximate non-shadow point. The detailed operation for shadow removal is given below. The shadow removal process is done by first identifying connected components (8-connectivity) in the binary mask, where each connected component represents a shadow. Then, for each shadow component, the algorithm computes the boundary of the shadow and calculates the slope of each boundary point. Next, a separate function called "remove" is called for each connected component to remove the shadow. The" remove" function takes the original image, the binary mask of the shadow, the x and y coordinates of the boundary points, the slopes of the boundary points, and a flag indicating whether to smooth the edges of the resulting image. Within the "remove" function, the algorithm first normalizes the input image and calculates the average pixel intensities of non-shadow areas and shadow areas. Then, it calculates the ratio of non-shadow pixel intensities to shadow pixel intensities. This ratio is used to approximate the non-shadow intensity of each pixel within the shadow area by multiplying the shadow intensity of each pixel by the ratio. Finally, the resulting image with the shadow removed is returned and displayed to the user.

Algorithm

Step 1: On running the GUI.m file in MATLAB the first step is to load the RGB image with shadow.

Step 2: To remove noise from the image, the system applies a Gaussian filter to the image.

Step 3: Split the RGB image into 3 channels and assign each of them to a respective variable.

Step 4: The Chromaticity function defined takes three arguments R, G, and B correspond to red, green and blue channels of the RGB image and calculates the Chromaticity values of the image by dividing the green and blue corresponding channels. Then it takes the logarithm of chromaticity values. The output of the function is two 1D arrays representing chromaticity values of the image in log space. This output is then converted to a 2-D Chromaticity vector.

Step 5: To find the optimal projection direction θ that maximizes the statistical coherence in the reflectance component, run a loop that iterates over the possible values of θ.

Step 6: For a given projection angle θ, the projection results in a scalar value for which a histogram is formed and entropy is calculated. The theta which results in the lowest value of entropy is the correct direction of projection. The projected vector is reshaped into a 2D matrix which is the illumination-invariant intrinsic image and bright pixels are added to the inherent image to match the brightness of the grayscale version of the input image.

Step 7: Then the mask is obtained by taking the difference between the Intrinsic image and the Grayscale of the original image. By applying thresholding on the mask, a binary shadow mask is obtained.

Step 8: By applying the mask on the image, the desired output is obtained, i.e., Shadows are detected in the image.

Step 9 The shadow mask and input image are then passed to the 'removeShadow' function defined.

Step 10: The function first uses the bwconncomp function to get connected components (8-connectivity) of the mask image. These connected components represent the shadows present in the image.

Step 11: For each connected component, the function creates a temporary binary mask (maskTmp) of the same size as the input mask matrix, and sets the pixels within the connected component to 1. It then uses the be boundaries function to obtain the boundaries of the shadow and calculates the slope of each boundary point.

Step 12: The function then calls another sub-function named "remove" that takes the input image, the binary mask, the x and y coordinates of each boundary point, and the slope of each boundary point.

Step 13: The remove function calculates the average intensities of the non-shadow pixels perpendicular to the shadow edges, as well as the average shadow intensity of the shadow pixels.

Step 14: The remove function then goes through each shadow boundary point, and calculates two points away from the shadow boundary point in the clockwise and anticlockwise direction, and finds the maximum and minimum intensity values of these two points. It then calculates the average non-shadow pixel intensities and the average shadow pixel intensities.

Step 15: After this, the remove function calculates the non-shadow pixel-to-shadow pixel ratio for each channel and uses it to multiply each shadow pixel with its respective ratio to get an approximate non-shadow pixel.

Step 16: Finally, the remove function returns the output image with the shadows removed.

Step 17: The main function then displays the output image.

IV RESULTS AND DISCUSSIONS

Shadow detection is done by performing Entropy

Minimization to find an Invariant image from an RGB image with shadows. These invariant images are also referred to as intrinsic images as they capture the intrinsic reflectivity of the objects in the image, independent of illumination. Subsequently, the detected shadows are removed using the relighting technique.

Figure 3: Image A, a Tower from Japan

Figure 3 shows a tower from Japan and another smaller building casting shadows. The tower casts a left-leaning long shadow and to the right of the tower, a small building casts a similar shadow.

For ease in selecting the required images to remove the shadow from and have control over output windows, a runtime graphical user interface is generated using GUIDE, an inbuilt UI design interface provided in MATLAB. The UI displays the Original Image, Shadow Mask & shadow Contour (From left to right).

Figure 4 shows the GUI interface which has three sections image, shadow mask, and shadow contour where the image is uploaded in the image section. A shadow mask will be applied to the input image in the shadow mask section and shadow will be detected in the red boundary in the contour section.

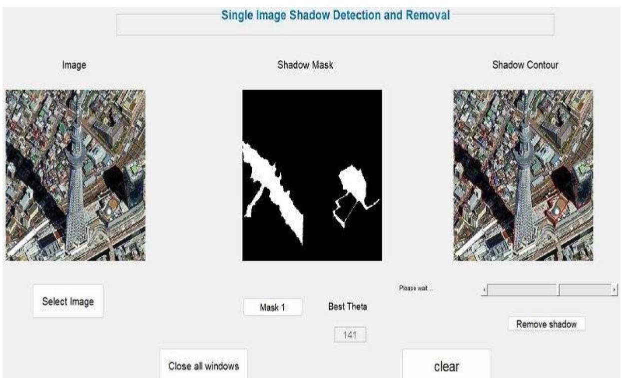

Figure. 4 Screenshot of GUI of Shadow Detection and Removal for image A

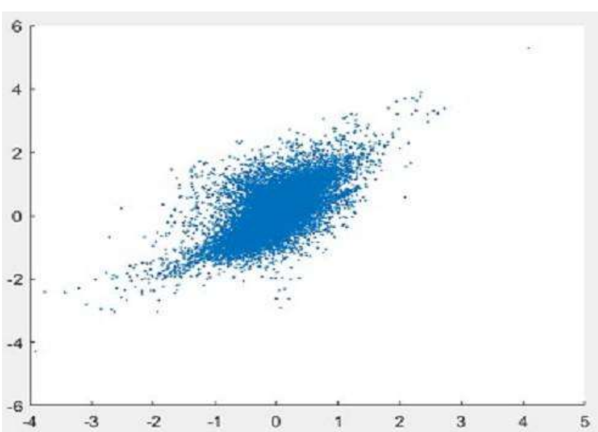

Figure 5 log chromaticity distribution of image A

In image A, a large part of the image is grey. Hence, in Figure 5, log chromaticity chart, the area corresponding to grey colour has more density of pixels.

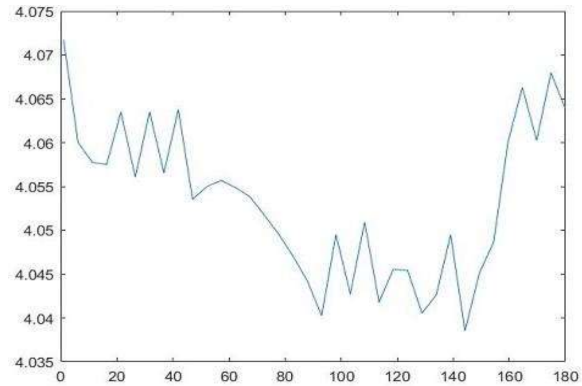

Figure 6 Illumination entropy of image A over angles 0^0 to 180^0

The shadow in the original image (A) is directed toward roughly 86^0. Hence the entropy becomes minimum at around 86^0.

The intrinsic image in Figure 7 is the illumination-invariant image of image A (fig 3.1). This image shows both - the shadowed and non-shadow areas at the same amount of illumination. This image will be used for the detection of shadow areas.

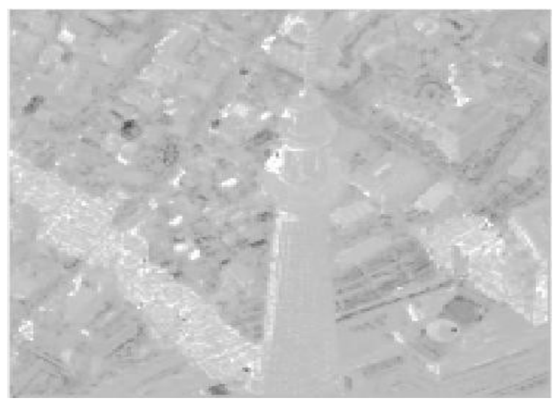

Figure 7. Intrinsic image of Image A

Figure 8. Shadow removal from image A.

Fig 8 is the image obtained after removing shadows from image A (figure 3). Here two major shadows have been removed – The shadow cast by the tower and the shadow of the nearby smaller building. There remains an imprint of the removed shadow, which leaves the scope for improvement of the algorithm.

Figure 9. Image B: Image for shadow detection and removal

A building having some shadowed portions and shadowed foreground is considered as Image B as shown in Figure 9 This is the Bodleian Library and the building and its front porch are covered in shadows.

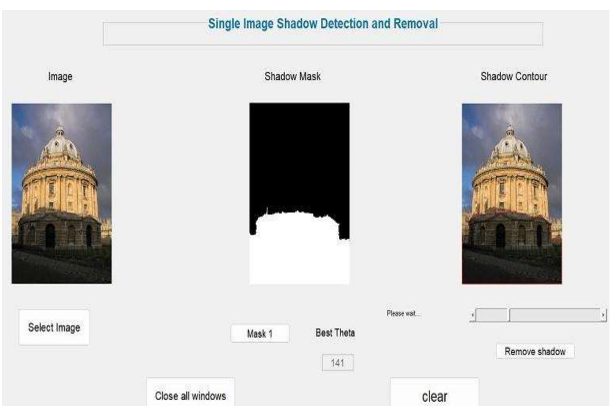

Figure 10. Screenshot of GUI of Shadow Detection and Removal for image B (Original Image, Shadow Mask & shadow Contour (From left to right))

For ease in selecting the required images to remove the shadow from and have control over output windows, a runtime graphical user interface is generated using "guide", an inbuilt UI design interface provided in MATLAB. The UI displays the Original Image, Shadow Mask & shadow Contour (From left to right). Figure 10 shows the GUI interface which has three sections image, shadow mask, and shadow contour where the image is uploaded in the image section. A shadow mask will be applied to the input image in the shadow mask section and shadow will be detected in the red boundary in the contour section.

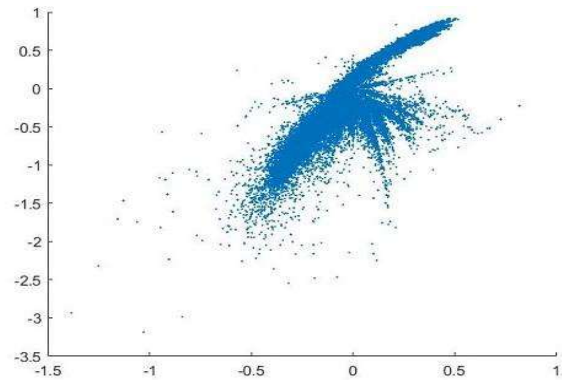

Figure11. log chromaticity Image B

The log chromaticity distribution plots the chromaticity of each pixel in the image as shown in Figure 11. Image B mainly contains grey clouds, a blue sky, buildings in a shade of yellow colour, and green grass. These colours have been reflected in the log chromaticity chart in a proportionate degree.

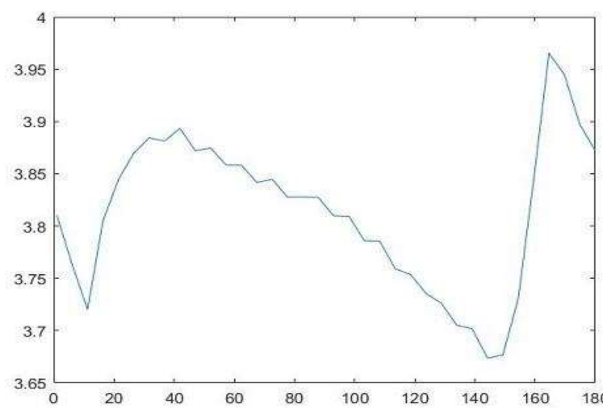

Figure 12. Illumination entropy of image B over angles 0 to 180˚

Figure 12 shows the angular distribution of entropy in Image B. The minimum entropy will indicate the direction of the shadow. For image B, the minimum entropy lies at 170˚ and that has been reflected in Figure 12.

Figure 13. Intrinsic image of image B

The intrinsic image in Figure 13 is the illumination-invariant image of image B (figure 9). This image shows both - the shadowed and non-shadow areas at the same amount of illumination. This image will be used for the detection of shadow areas.

Figure 14. Result of Shadow removal from Image B (final result)

Figure 14 shows the result of shadow removal from Image B. Notice that the shadow lower portion of the building in Image B (figure 9) has been removed in Figure 14. Also, the shadows that were present in the foreground have been removed to a large extent. While a lot of shadows have been removed, some traces of the shadow remain. Work toward overcoming this remains to be done.

IV. CONCLUSION

The demonstrated approach showed good performance in shadow detection and removal while being lightweight, simple to apply, and with little time for processing. From the analysis of various results, we can conclude that more variation in illumination generates a better result. The advantage of the demonstrated algorithm is the ability to detect and remove shadows while consuming low computational and time resources.

While some results still contained traces of removed shadow and residual from the processing of the image, most shadows were removed. The work to improve the results by dealing with these components remains to be done.

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REFERENCES

1. Pandit, A., & Singh, A.K. (2019). Shadow Detection and Removal Techniques: A Perspective View. *International Journal of Trend in Scientific Research and Development* Volume-3 | Issue-4, June 2019, pp. .2456-6470,
2. Ramachandran, . Chitra. K., ahul. A. Comparison of Shadow Detection Removal and Reconstruction Methods.International Journal of Science Technology and Engineering, Vol. 1,Issue 10,2349-784X, April 2015.
3. Blajovici, C., Kiss, P. J., Bonus, Z., & Varga, L. (2011). Shadow detection and removal from a single image. *Proceedings of 19th SSIP, 19th summer school on image processing. Szeged, Hungary*, 7-16.
4. Khan, S. H., Bennamoun, M., Sohel, F., & Togneri, R. (2015). Automatic shadow detection and removal from a single image. *IEEE transactions on pattern analysis and machine intelligence*, *38*(3), 431-446.
5. Xu, L., Qi, F., & Jiang, R. (2006, October). Shadow removal from a single image. In *sixth international conference on intelligent systems design and applications* (Vol. 2, pp. 1049-1054). IEEE.
6. Vicente, Tomas F. Yago, Minh Hoai, and Dimitris Samaras. "Leave-one-out kernel optimization for shadow detection and removal." IEEE Transactions on Pattern Analysis and Machine Intelligence 40.3 (2017): 682-695.
7. Hu, X., Wang, T., Fu, C. W., Jiang, Y., Wang, Q., & Heng, P. A. (2021). Revisiting shadow detection: A new benchmark dataset for complex world. *IEEE Transactions on Image Processing*, *30*, 1925-1934.
8. Zheng, Q., Qiao, X., Cao, Y., & Lau, R. W. (2019). Distraction-aware shadow detection. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition* (pp. 5167-5176).
9. Mostafa, Y., & Abdelhafiz, A. (2017). Accurate shadow detection from high-resolution satellite images. *IEEE Geoscience and Remote Sensing Letters*, *14*(4), 494-498.
10. Asaidi, H., Aarab, A., & Bellouki, M. (2012, May). Shadow detection approach combining spectral and geometrical properties. In *2012 International Conference on Multimedia Computing and Systems* (pp. 389-393). IEEE.
11. Murali, S., & Govindan, V. K. (2013). Shadow detection and removal from a single image using LAB color space.

Cybernetics and information technologies, *13*(1), 95-103.

12. Russell, M., Zou, J. J., & Fang, G. (2015). Real-time vehicle shadow detection. *Electronics Letters*, *51*(16), 1253-1255..
13. Finlayson, G. D., Drew, M. S., & Lu, C. (2004). Intrinsic images by entropy minimization. In *Computer Vision-ECCV 2004: 8th European Conference on Computer Vision, Prague, Czech Republic, May 11-14, 2004. Proceedings, Part III 8* (pp. 582-595). Springer Berlin Heidelberg.
14. Guo, L., & Du, M. H. (2012, December). Moving cast shadow detection based on region intrinsic image with entropy minimization. In *Proceedings of 2012 2nd International Conference on Computer Science and Network Technology* (pp. 2126-2130). IEEE.
15. Nair, V., Kosal Ram, P. G., & Sundararaman, S. (2019). Shadow detection and removal from images using machine learning and morphological operations. *The Journal of Engineering*, *2019*(1), 11-18.
16. Nikkil Kumar, P. C., & Malathi, P. (2020). A survey on various shadow detection and removal methods. In *Computational Vision and Bio-Inspired Computing: ICCVBIC 2019* (pp. 395-401). Springer International Publishing.https://doi.org/10.1007/978-3-030-37218-7_45
17. Feng, J., Kim, Y. K., & Liu, P. (2022). Image shadow detection and removal based on region matching of intelligent computing. *Computational Intelligence and Neuroscience*, *2022*. https://doi.org/10.1155/2022/7261551
18. Koutsiou, D. C. C., Savelonas, M. A., & Iakovidis, D. K. (2024). SUShe: simple unsupervised shadow removal. *Multimedia Tools and Applications*, *83*(7), 19517-19539.https://doi.org/10.1007/s11042-023-16282-0
19. Baba, M., Mukunoki, M., & Asada, N. (2004). Shadow removal from a real image based on shadow density. In *ACM SIGGRAPH 2004 Posters* (p. 60).
20. Dhingra G, Kumar V, Joshi HD (2021) Clustering-based shadow detection from images with texture and color analysis. Multimed Tools Appl 80(25):33763–33778.
21. Finlayson G.D, Hordley S.D, Drew MS (2002) Removing shadows from images. In: Proceedings of the Eur Conf Comput Vis (ECCV), pp 823–836.
22. Finlayson G., Hordley S., Lu C, Drew M. (2005) On the removal of shadows from images. IEEE Trans Pattern Anal Mach Intell 28(1):59–68.
23. Hu X, Fu C-W, Zhu L, Qin J, Heng P-A (2019) Direction-aware spatial context features for shadow detection and removal. IEEE Trans Pattern Anal Mach Intell 42(11):2795–2808.
24. Hu X, Jiang Y, Fu C-W, Heng P-A (2019) Mask-shadowgan: learning to remove shadows from unpaired data. In: Proceedings of the IEEE/CVF Int Conf Comput Vis (ICCV), pp 2472–2481.
25. Le H, Samaras D (2019) Shadow removal via shadow image decomposition. In: Proceedings of the IEEE/CVF Int Conf Comput Vis (ICCV), pp 8578–8587.
26. Le H, Samaras D (2020) From shadow segmentation to shadow removal. In: Proceedings of the Eur Conf Comput Vis (ECCV), pp 264–281.
27. Wu, W., Wu, X. & Wan, Y. Single-image shadow removal using detail extraction and illumination estimation. *Vis Comput* **38**, 1677–1687 (2022). https://doi.org/10.1007/s00371-021-02096-4.
28. Finlayson, G.D., Drew, M.S. & Lu, C. Entropy Minimization for Shadow Removal. *Int J Comput Vis* **85**, 35–57 (2009). https://doi.org/10.1007/s11263-009-0243-z