CSE-4019 Image Processing
Project Report

Image Shadow Removal Using Non-Shadow Mapping

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DECLARATION

I hereby declare that the report titled "**Image Shadow Removal Using Non-Shadow Mapping"** submitted by me to VIT Chennai is a record of bona-fide work undertaken by me under the supervision of Dr Geetha, School of Computer Science and Engineering, Vellore Institute of Technology, Chennai

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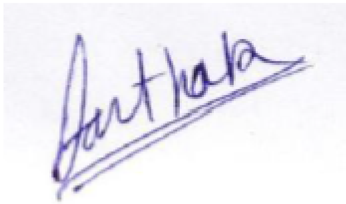

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<u>CERTIFICATE</u>

Certified that this project report entitled "**Image Shadow Removal Using Non-Shadow Mapping"** is a bonafide work of **Karmabir Chakraborty (19BCE1439), Venkata Ashish Nunna (19BCE1256), Sarthak Tyagi(19BCE1666), Aryan Arora (19BCE1479)** and they carried out the Project work under my supervision and guidance for CSE-4019(Image Processing)

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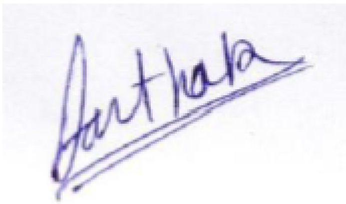

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ABSTRACT

Gathering information from images has become an important aspect of technology and its advancement. Henceforth, we extract a lot of sensitive information from images that can be further used as evidence or to infer some really important research result. In some situations, shadows darken the area of concern eliminating the correct result and raising a possibility of a wrong inference. Therefore, we need a shadowless image for processing results. Shadow removal has evolved as a pre-processing step for various computer vision tasks. Our method considers the shadow part of the image and finds it's non shadow counterpart. It uses non shadow mapping to lighten the shadow regions with the help of histogram matching. It also preserves the texture of the image to much extent by considering gradient and texture features. Our method is evaluated on three metrics in order to analyse its accuracy.

CONTENT TABLE

INTRODUCTION

Shadows have their own limitations and advantages. But they may pose a problem in various computer vision algorithms like edge extraction, object identification, object counting, and image matching. For example, darker regions in the image caused by cast shadows can introduce spurious segments in segmentation algorithms. In digital photography, shadows may be considered as artifacts in the image that need to be removed, whether for enhancing certain parts of the image or simply for aesthetic reasons. Shadow regions are believed to be particularly formed by reduction of illumination field, resulting in changes of image intensities by multiplicative scalars. We assume the shadows to be uniform and according to this we infer that we can capture the change in intensity with only a single factor. But in practice, this is not the case. Shadowing is a phenomenon that arises naturally due to an opaque object obstructing the light and the surface.

Shadows can be classified into soft and hard shadows. As the name suggests hard shadows are shadows with high densities, their surface texture is nearly destroyed and soft shadows are shadows with low densities, their boundaries are usually diffused with the non-shadow regions. The shadows generated by the interruption of a non-point illumination source have two distinct regions namely, umbra and penumbra. Although shadows can provide useful cues for estimating scene illumination, finding the geometry of object casting the shadow, locating the light source and so on, their presence may cause hindrance in various image and video processing tasks, such as segmentation, object detection, and video surveillance. Therefore, the removal of shadows is inevitable for the flawless execution of these algorithms. Understanding the properties of shadows is inevitable in identifying the shadows in an image. They exhibit a number of properties that differentiate them from the non-shadow areas in an image. It is observed that shadow regions have lower values for RGB, grey level intensity, standard deviation, variance, local maximum, and brightness since these values depend on the illumination and the shadow regions are less illuminated than the surroundings. The hue value that indicates the dominant colour of a surface remains nearly the same in both shadow and shadowless regions. Difference in skewness values arises due to differences in the asymmetries in shadow and non-shadow regions. Since shadow areas are darker, their entropy and saturation values are less. Many of these properties are explored by the researchers to separate the shadow regions from the shadowless regions in an image.

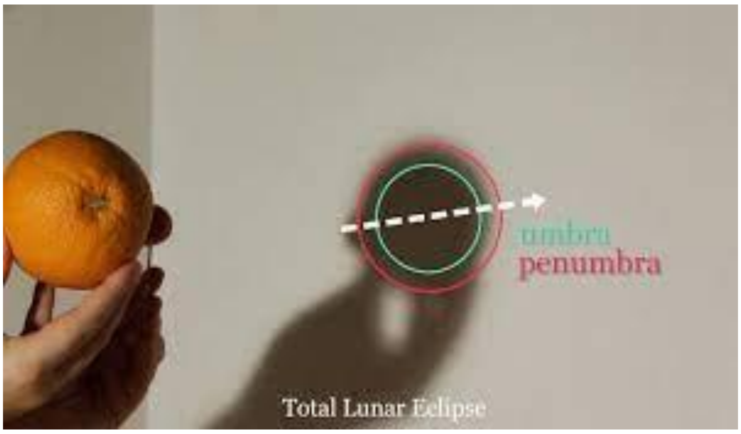


Fig.1. Umbra and Penumbra region

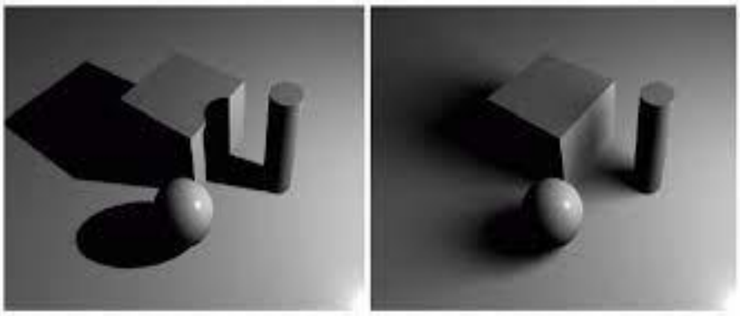


Fig.2. (A) Hard Shadow (B) Soft Shadow

OBJECTIVES OF THE WORK

The key objectives of our shadow removal approach are as follows:

- To identify the shadow regions.
- To find the non-shadow mapping of the shadow pixel.
- To manipulate the shadow pixel according to its non-shadow mapping for an effective shadow removal.
- To preserve the texture of the image.

PROPOSED WORK

Shadow area detection and preservation of texture are the key goals of our algorithm. The images with different textures generally create a challenge to most of the shadow removing algorithms as this sudden change of texture can create abrupt change in pixel values due to which they can be classified as the shadow pixels and can give a very different output.

The whole shadow detection and removal procedure is divided into three major categories:

1) Area matching for texture preservation.
2) Shadow pixel detection.
3) Mapping shadow pixel to non-shadow similar pixel for shadow removal.

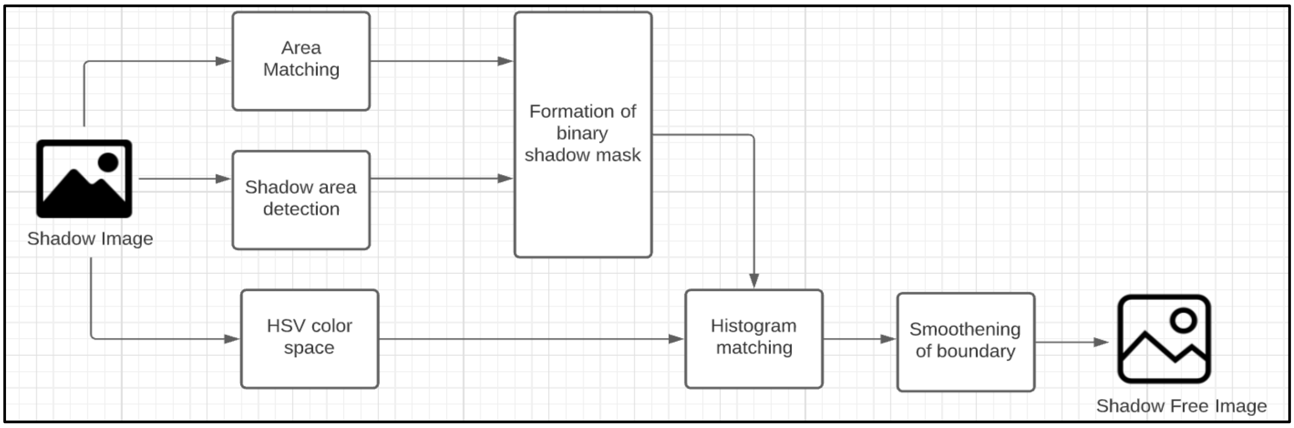
Before entering into these three sections, image segmentation is the first step of our algorithm. We use a clustering technique introduced by Fukunaga and Hostetler and is called mean shift clustering. In this, pixels with similar colours in RGB colour space are gathered into the same cluster. Pixels are recoloured according to their cluster, resulting in the segmented image. The mean-shift method models feature points using a probability density function where local maxima or modes correspond to dense areas. Then the gradient ascent is performed on the estimated density of each data point until the algorithm converges. All data points belonging to a particular stationary point are grouped into a single cluster. The EDISON (Edge Detection and Image Segmentation System) developed in the Robust Image Understanding Laboratory at Rutgers University is used to perform the mean shift segmentation.

Fig 3.1 Original image and it’s shadow mask

The shadow image and segmented image is taken as an input for all the three sections. The area matching algorithm first segments the image and then helps in recognizing the nearest most similar segment and degree of similarity of a particular segment with respect to the other segments present in the image. This will help in getting the information of the neighbouring pixel which can help in reducing the chances of misclassification of the pixels as shadow or non-shadow pixel. Next is the shadow area detection part which takes the original shadow image for detecting the shadow pixel. First the conversion of image into YCbCr plane and HSI plane takes place for labelling the pixels as shadow pixels, and calculating near and between matrices for feature restoration according to the similar regions. A refuse matrix is also calculated to restrict the non-shadowed regions. A shadow mask is generated after labelling the pixels. The removal part also takes the original image and converts it into HSV colour space. Each channel of the HSV image is individually processed and, in each processing, histogram matching takes place between the original image and the template formed in the detection part. The basic idea of shadow removal is to find non shadow mapping for the shadow pixel and change accordingly. In the end, the image channels are recombined and converted into RGB colour space. The shadow boundaries are smoothened by applying the gaussian filter and then taking the intersection of the output image and blur image.

Area matching for texture preservation

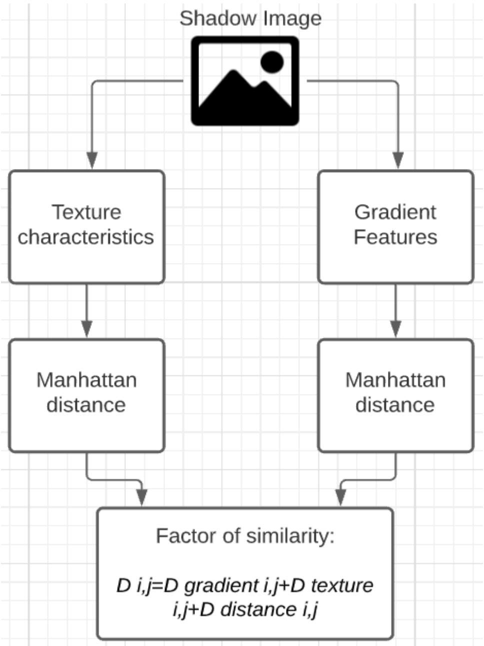
One of the major challenges for an image restoration or manipulation algorithm is to preserve the original details like texture after the processing. As we know that the colour and saturation changes for a shadow and non-shadow pixel, we cannot consider them for the feature extraction. For this very problem, we have considered image gradient features and texture



characteristics as they don’t change with shadow and are shadow invariant as the gradient change of gradient feature map area and the texture feature map show that they are not much affected by the shaded area. When the two areas have the same texture, the similarity of gradient between the domains is stronger. So to get the similarity, at first we calculated the gradient histogram for all the regions of the image and then after that, we calculated the Manhattan distance between the two area histograms for finding the most similar region. For texture characteristics, we used a special method of textons and just like the previous one, we calculated the Manhattan distance between the two area histograms.

Manhattan distance = | X1 - X2 | + | Y1 - Y2 |

After calculating and extracting both the features for all the regions, we have to ensure local consistency also. For this, we found the distance between the two regions also by finding their centroids and computing the distance between them.



After getting all the three values, the factor of similarity between the two regions i and j is calculated as follows:

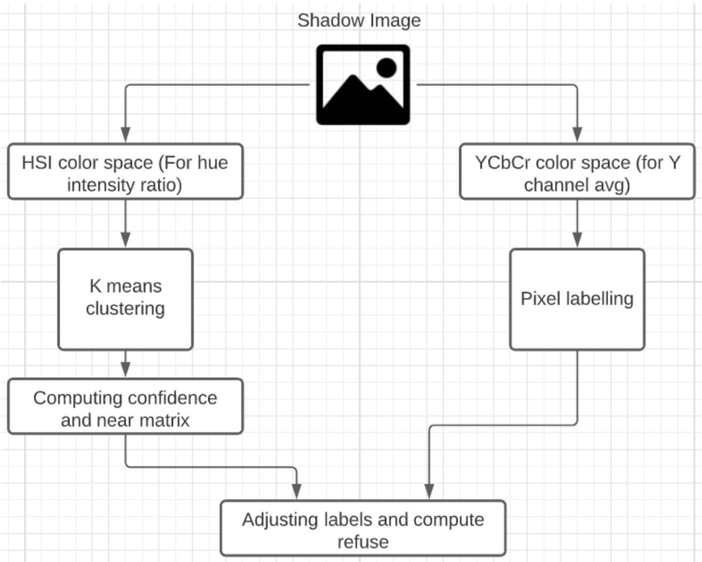
D (i,j) = D gradient (i,j) + D texture(i,j) + D distance (i,j)

Shadow pixel detection and labelling

In this part, we have two types of processing of the image. The first one is to label the shadow pixels on the basis of the shadow features and the second one is to label the shadow pixels on the basis of the mutual constraints between the regions of the image. The image is converted into the YCbCr plane and HSI plane. Shadow regions are usually darker than their surroundings and that's why the creation of shadows is often attributed to the change in illumination. To extract the illumination information from the input shadow image, we transform it into YCbCr colour space where the Y channel is the illumination, Cb is the blue difference, and Cr is the red difference. According to [6], when a Y channel value is less than 60% of the average of the whole Y channel, the area can be considered as the shaded area and that pixel can be labelled as shadow pixel. Hue is considered as the base variable for shadow detection in most of the shadow detection algorithms. But we considered the hue over intensity ratio method for a better result. That's why after converting it into the HSI plane, we extract the H and I value and normalize it. Then the R (x,y) is calculated as follows:

$$R(x, y) = He(x, y) / Ie(x, y)$$

where H is hue and I is intensity.



For the ratio R of all the regions, we use k-means clustering to find the centre of the shadow and non-shadow region. From this, we get a C shadow, C non-shadow and the standard deviations for both the centres. Hence for each region ratio R(i), we can calculate the confidence of that region belonging to the C (shadow) or C (non-shadow) part. For each area S(i) which we calculated in YCbCr planes, we constructed a Refuse matrix which represents whether it is a shadow area or not as other areas are prohibited and is initialized to 0. After computing the R (i) ratio and the confidences, if Refuse = 0 then label the pixel as shadow pixel. Now for this pixel check the near (i), neighbouring pixel information and mark its j.

Compare R(i) and R(j) to check whether S(i) and S(j) are light opposite areas. If yes then update the Refuse as 1. This update is necessary as if some of the pixels can be misclassified as shadow pixels due to sudden texture change. After performing all these updates, a shadow mark is created which distinguishes the shadow pixels for the non-shadow one. We use it as a template in the shadow removal part for mapping those particular shadow pixels to its corresponding non shadow part.

Mapping of shadow pixel to non-shadow similar pixel for shadow removal

This mapping and shadow removal takes place in the HSV (Hue, Saturation, Value) colour plane. For an image, hue represents the basic colour of the pixels of the image, saturation represents the greyness, and the value represents the brightness. Since hue is unaffected by changes in illumination, we assume that shadows do not alter the hues of pixels as they are caused by changes in illumination. So, we use this colour space for our histogram matching. The main idea is to find the corresponding S (j) non shadow pairing of the shadow region S (i). We use S (j) to brighten the S (i) region.

Histogram matching

Histogram matching is the transformation technique in which an image's histogram matches a specified histogram. The well-known histogram equalization method is a special case in which the specified histogram is uniformly distributed. Now as we have created a template in the form of a shadow mask at the time of detection, we can use it to lighten the shadow areas. The major steps of histogram matching are as follows:

1) Histogram of feature (i) with the number of stripes equal to the template T histogram H(T) is calculated as H(i).
2) The cumulative histogram CH(i), CH(T) is calculated for H(i) and H(T).
3) For each strip x in CH(i), the stripe number y with the smallest difference from CH(T) is calculated.
4) Now move each stripe x to the position of y as a whole.

All the three channels of HSV colour space are adjusted using this histogram matching.

All the three channels are then merged again and converted into RGB colour space. The boundary of the shadow is smoothed to give an even texture to the whole image. For this, first the gaussian filter is applied to the RGB image to get the smooth pattern of the image. Then the intersection boundary of shadow and non-shadow areas is calculated and then the pattern is used to smoothen the boundary pixels.

ALGORITHM USED

STEP 1: User enters the Path of the Image.

STEP 2: Read the Image.

Shadow Detection

STEP 3: Use the mean shift algorithm to segment the image. Each area is denoted as Si and the centre is C_i, totalling n areas;

STEP 4: According to Eq (1), calculate the difference D (i, j) between S_i and S_j to calculate the corresponding area with the highest similarity for each area, which is recorded as $Near_i$. At the same time, record the information label of whether the area i is a shadow, and it is initialized to 1;

STEP 5: For all R_i, 1 <i <n, use k means clustering to calculate two centres C(Shadow) and C (lit), which respectively represent whether they are the feature centres of the shaded area. Assuming that the feature R obeys a normal distribution, the standard deviations Std Shadow and Std (lit) corresponding to C(Shadow) and C(lit) are calculated. Therefore, for each Ri, the confidence.

STEP 6: For each area S_i, $Refus_i$ represents whether it is called a shadow area because other areas are prohibited, and it is initialized to 0.

Histogram Matching

STEP 7: Calculate the histogram $Hist_i$ of Features with the number of stripes equal to T.

STEP 8: Calculate cumulative histograms Acc_i, Acc_T for $Hist_i$ and $Hist_T$ respectively;

STEP 9: For each fringe p in Acc_i, calculate the fringe sequence number q with the smallest difference between Acc_t;

STEP 10: Move each stripe p to the position of q as a whole.

Removal

STEP 11: Calculate the shadow detection result label, and convert the image to HSV space at the same time;

STEP 12: Repeat steps 13 - 15 for each shadow area S_i.

STEP 13: For the area S_i, find that Sj is full $label_j = 1$ and D(i,j) is the smallest, use S_j to brighten S_i

STEP 14: For each channel H, S, I of the HSV color space, calculate the histogram Hist(H,j), Hist(S,j), Hist(I,j) of S_j.

STEP 15: Using Hist(H,j), Hist(S,j), Hist(I,j) as the template for matching the histogram, adjust the three features of Si to make the feature distribution close to the template.

STEP 16: Convert the image to RGB space.

STEP 17: Calculate the intersection boundary between all shadow areas and non-shaded areas in the image, and then smooth all the boundaries.

QUANTITATIVE ANALYSIS

To analyse the accuracy of our method, we use three metrics:

Root mean square (RMSE)

RMSE is the square root of the mean of the squared error. The error for an image is computed as the per-pixel difference between the shadow-free ground truth and the shadow removal output. Let G(i) and O(i) indicate the intensity of the ith pixel in the ground truth and the test result images, respectively. Then the formula for RMSE is:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(G_i - O_i)^2}$$

A lower value indicates that the output image is more similar to the ground truth as RMSE is an error measure.

Peak signal to noise ratio (PSNR)

PSNR is used to find peak error. It computes the peak value of SNR, in decibels, between two images. The value of PSNR ranges between 0 and infinity. A higher PSNR value signifies better quality of the output image. For calculating PSNR, first we have to compute mean squared error (MSE) as:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(G_i - O_i)^2$$

where Gi and Oi indicate the intensity of the ith pixel in the ground truth and output images. Now the PSNR can be calculated as follows:

$$\mathrm{PSNR} = 10\ \log(\frac{\eta^2}{\mathrm{MSE}})$$

where η denotes the maximum possible pixel value in the images.

Structural Similarity Index (SSIM)

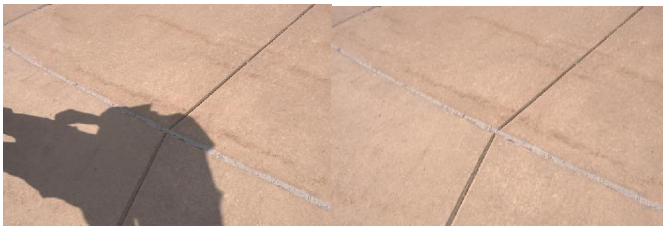
SSIM is a metric used to compute the correlation between two images. It is considered to be a measure that is closest to the human visual system. The SSIM formula is a weighted combination of comparisons of three elements between the images, namely luminance, contrast, and structure and is given as follows:

$$\mathrm{SSIM}(G, O) = \frac{(2\mu_G\mu_O + c_1)(2\sigma_{GO} + c_2)}{(\mu_G^2 + \mu_O^2 + c_1)(\sigma_G^2 + \sigma_O^2 + c_2)}$$

where G and O are the shadow-free ground truth and the shadow removal output, respectively, μG and μO are the mean values of G and O, $\sigma 2$ G and $\sigma 2$ O are the variances of G and O, and σGO is the covariance of G and O. c1 and c2 are variables computed using the dynamic range of pixels.

RESULTS

The successful working of the proposed shadow removal algorithm has been implemented and has been tested with various images to prove its efficiency. The detection aspect can ensure the consistency of the image to a certain extent through mutual restriction of the same area of the image. By brightening the shadow area with the similar section of the image can minimize the removal operation on the shadow area by the influence of non-shadow area of the other section of the image. In case of complex images, the accuracy of the algorithm is not very good.



a) Original image b) Ground truth

c) Image after shadow removal d) Shadow mask

Image	**RMSE**	**PSNR**	**SSIM**
Original shadow image	37.23	36.03	0.89
Non shadow image after shadow removal	12.78	42.43	0.93

These quantitative results showed that our image after shadow removal showed more similarity with the ground truth image.

LIMITATIONS:

- It works for shadows images having two or three different textures.
- If there is a dark object in the shadow, it cannot classify the shadow correctly.
- It doesn’t work for rigid surfaces because it fails to get the whole shadow into account.
- It supplies the mean of the surrounding pixels to the shadowed region.
- It cannot fully remove the shadow border and uses a gaussian filter for smoothening which affects the PSNR value of the image.
- It doesn't give a proper result for an image with many color classes.

CONCLUSIONS

Shadows may lead to the incorrect execution of certain tasks in computer vision, such as object detection and counting. They are also a challenge in the digital forensic field as they can be used for data hiding. To tackle this challenge, we proposed a method which involved three color spaces to remove shadows from an image. The texture of the image is preserved to much extent by considering the gradient and the texture features with the help of extensive methods from. Our method is based on MATLAB and does not require prior training on the dataset. It works on both hard shadows and soft shadows with texture. Moreover, it also smoothened the boundary after removing the shadow from the original image to make the image look more even. But if there is a dark object covered entirely by the shadow, sometimes it is considered as the shadow and it gives the wrong result. Overall, this method works for shadow images with two or three textures and it reduces the overall RMSE of the image.

FUTURE WORK

The future work in our method includes the usage of different techniques like bi directional smoothing to make the shadow boundaries smooth according to the texture. Another modification can be increasing the efficiency as this method takes time for processing. Fuzzy C clustering can also be used for segmentation of the image. Our method was not able to perform well for the images having many colours.

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