



Shadow Detection and Removal Methods on an Image documents Using GMM Model

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Abstract— Shadows appear in photos due to uneven lighting. Shadow reduction from photographs and videos has lately garnered attention due to the harmful effects shadows have on many Computer Vision operations. Videos can remove shadows, but images cannot. Shadow identification and elimination from single images is difficult because all the information needed to discover and illuminate the shadow region must come from one image. This thesis identifies and removes shadows from a single image.

The contribution is a quick interactive gaussian mixture model (GMM) shadow reduction technique. Strokes applied to the shadow region and its corresponding non-shadow region provide the system with crude user input. Pixel quaternions in the YCbCr colour space are rotated to produce an illumination-invariant image. Compared to illumination-invariant photos made using the current techniques, this image is shadow-free and has higher visual quality. Following that, colour transfer from the input shadow image is used to restore the true colours in the image. The suggested solution does not require the detection of shadows before their removal and generates output without any shadows in real time.

Index Terms—Shadow, Shadow Detection, Shadow Removal, gaussian mixture model (GMM), Evaluation Metric.

I. INTRODUCTION

An important problem in machine vision systems is the detection and elimination of shadows. The shadow of a picture contains details about an object's size, position, and light source. One such application is determining a building's height from its shadow. The shadows in an image are undesirable because they degrade the output when the image is processed for object detection, scene surveillance, segmentation, or other similar applications. An image's shadows can alter the contour of a target object to make it easier to detect. This issue can be avoided by identifying shadows and separating them from the target item [1-2].

In this study, three domains are primarily covered. The image's colour segmentation is the initial domain. Shadow detection is the second domain, while shadow removal from the image is the third domain. Static images are present in all three domains. The definition of a shadow is an obstruction in the path of light. Shadow areas become lighter due to ambient light. Some of the literature on shadow detection and eradication provide the relevant definition of a shadow (Scanlan 1990; Salvador 2001; Etemadnia 2003; Yao 2004) [3].

One simple way for detecting shadows is based on the idea that while shadows dim the region, the colour attributes remain unchanged. Shadow detection also makes advantage of the texture attributes. the implication that shadow areas exhibit a consistent textural characteristic across all frames and in the relevant adaptive background. Additionally, they look at texture descriptors for foreground pixels linked to the background that are darker. The techniques presume that the background value is linearly attenuated from the shadow regions. Some techniques for detecting shadows combine their geometrical and photometrical characteristics.

The appropriate information about the image cast in the shadows. Regarding the placement and shape of items in an image, as well as the features of surfaces and light sources, shadows provide useful information. Despite this, shadows alter the detected shape and colour in real-world applications, presenting a deformity during the object detection process. The issue of shadow detection and removal is being addressed in part because of this. To aid in the process of image analysis, image segmentation divides a picture into groups of homogenous or discontinuous sections based on some characteristic or calculated property, such as colour, texture, or grey level. The segmentation approaches make use of the pixel relations' similarity and discontinuity features. Methods of segmentation based on edges or boundaries exploit the discontinuity property. The region-based segmentation methodologies use similarity or homogeneity methods. The segmented region is sometimes either bigger or smaller than the real image, which is a problem. The edges of the segmented region might not be linked. Some photos have too many and too few segmentations. In some circumstances,

it might be exceedingly challenging to locate the image's edges. The gradient function for some algorithms cannot be changed, leading to unfavourable outcomes. In the region-based technique, the seed value used is occasionally incorrect [4-5].

The shadow intensity is determined by the shadow scale factor. When the intensity varies in the shadow region, there are more unknowns regarding the shadow scale factor than there are when the shadow is uniform. The type of surface, the geometry of the item, and their interaction with the source of illumination are all factors in the shadow-removal process. Since self-shadows and shading typically result from a direct light source and infrequently from ambient light, the shading information is not present in the shadow image. As a result, eliminating the shadow does not bring back the shading information from the original image.

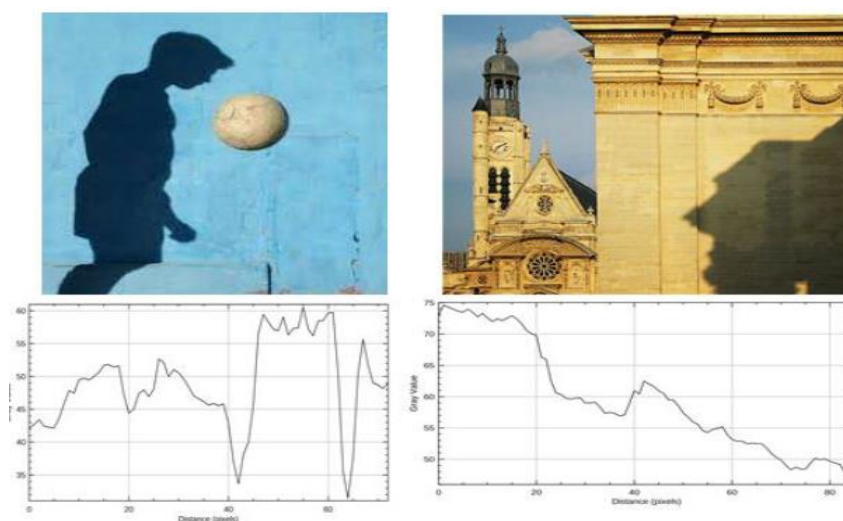


Figure 1: Uniform and Non-Uniform shadows

When an object blocks the path of light from a source (or from more than one source), it causes shadows to form on the surface. While shadows can offer helpful hints about scene illumination, object geometry, and light source location, their presence can have a negative impact on a number of image processing and video processing tasks, including segmentation, object detection, and video surveillance. The shadow region may be incorrectly identified as an item or as a component of an object during picture segmentation and object detection [6]. Due to shifting shadows, the detection of moving objects in a video clip may potentially produce inaccurate findings. As a result, the elimination of shadows is essential for the proper operation of these algorithms. Shadow removal is added into the pre-processing stage of these apps because it tries to improve photos and videos to make them appropriate for Computer Vision jobs.

Examples to demonstrate the adverse effect of shadows in the following Computer Vision tasks:

- scene interpretation
- face recognition
- optical character recognition
- target detection
- object counting
- object detection

Formation of Shadow

Because an object is obstructing the light source, a shadow is created. The two types of shadows are self-shadow and projected shadow. On the sides that are not facing the source of illumination, self-shadows appear. The cast shadow is created when the shadow of one item lands on that of another. Umbra and Penumbra are included in cast shadows. The umbra region of the shadow is created when all light is blocked, whereas the penumbra is created when just some light is blocked. The umbra zone totally obscures the light source, while the penumbra region only partially does so. According to Jiang and Ward (1992), penumbra is produced by an area light source, and umbra by a point light source [7].

Figure 2 depicts the creation of a shadow. The penumbra is depicted by the lightly tinted area, while the umbra is shown by the dark area. The shadow is shaped exactly like the thing obstructing the light. Numerous different effects can be created depending on the light source or sources.

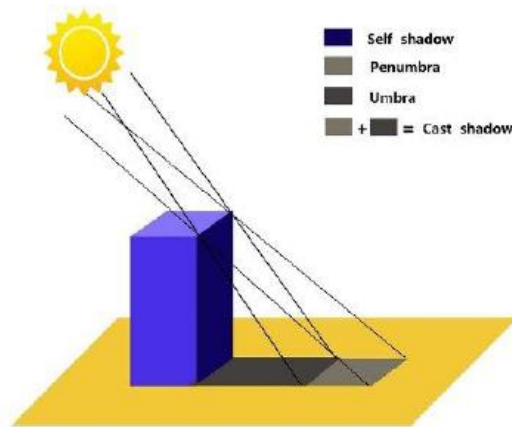


Figure 2: Shadow Formation

Under the impact of sunlight, a shadow will be generated, most likely formed in relation to the moving object, and this will result in incorrect detection of the item. As a consequence, the result of a shadow is typically mistaken for the object, which has an effect on moving object tracking. So, it will lead to an inaccurate identification or analysis of the moving object as a result of this. Refining the vision of computer vision tasks such as video surveillance, traffic monitoring, segmentation, and tracking all play an important part in the process.

Types of Shadows

A region that is said to be in the shadow is one in which light coming directly from a lighted source is unable to reach due to the presence of an item that blocks the path of the light. When working with photographs taken both outside and inside, the elimination of shadows following their detection is an essential step. The removal of the shadow cast by a moving item should always be performed in the direction of the moving object sequence, as this is an essential stage in the image processing process [8].

II. LITERATURE REVIEW

We can detect and precisely locate shadows in an image thanks to the properties found in the pixels of the shadow region. The features of an image include colour, edge, photometric characteristics, geometry, texture, shadow variant, and shadow in variant properties. The applicability of the characteristics varies depending on how they are used. While some techniques train a classifier based on features and use that classifier to identify the shadow pixels and regions, other techniques use the features to identify the shadow regions. The technique that use feature-based shadow detection identifies numerous features that can work effectively together to detect shadows. With just one feature, shadow identification is really challenging. Geometric and colour invariant traits were exploited in a multi-stage approach by (Salvador et al., 2004). The c1c2c3 colour invariant model and the object's shadow position are used to propose and verify the straightforward hypothesis that shadow areas of the image are darker than other areas of the image. The approach's biggest flaw is that soft shadows aren't correctly identified. By combining the illumination invariant, illumination direction, and nearby edge patch similarity information, (Wu et al. 2005) proposed a method for shadow identification. An SVM was trained to determine whether the edge patch was in shadow or not. The spatial patch smoothing method further improved the outcome [9].

According to Sanin et al. (2012), the categorization of shadow detection methods based on characteristics has a more positive effect. Based on the geometry, chromaticity, physical characteristics, and texture, the shadow detection techniques were divided into categories. For the purpose of locating and eliminating shadows, Hakima et al. (2012) combined geometrical and chronometric analyses. Spatial and temporal analysis is used to pinpoint the shadow zone. The geometric objects themselves are not necessary for the proposed method to work. The analysis of RGB colour data based on threshold and intensity is used to categorise shadows at the pixel level. By Li et al. (2018), geometric and textural features are merged. By applying threshold segmentation to the spectral characteristics, a shadow mask is produced. Combining the geometric and textural aspects enhances the shadow mask [10].

Guo et al. (2013) detected and eliminated shadow from images using a region-based technique. The image is divided into segments, and pairwise classification is carried out using materials and lighting conditions that are similar. According to their illumination and material, a pair of regions are found to be highly likely to be comparable to one another. The classification outcome results in the creation of a segment graph. The shadow zone is eliminated by relighting each pixel with both direct and ambient light based on the shadow coefficient and the ratio of direct to ambient light. The graph cut approach solves the problem of labelling with shadow and without shadow. The findings of the detection are further refined via image matting [11].

A approach for shadow removal that incorporates texture and intensity data is suggested by Tian et al. (2016). The programme learns to modify the illumination quickly. By fusing foreground mask and textured information, false positive areas are eliminated. The texture difference is determined using the gradient value. Each pixel of the foreground region's normalized cross correlation (NCC) of intensities between the current frame and the background image is determined. If both NCC and intensity are more than or equal to the threshold value, the pixel is considered to be a shadow [12].

III. DYNAMIC SHADOW DETECTION

There are various shadow detection strategies [13-14] and removal techniques that can be used to eliminate the shadow from the image.

The background subtraction and frame difference are used to detect a moving object in a static scene but in a sudden change in background i.e. light variation, the Gaussian distribution-based background modelling is very useful which is shown in Fig.3. In some scenes containing appearance change in this case single Gaussian distribution modelling is not used but a mixture of gaussian is used for moving object detection which is shown in figure 4.

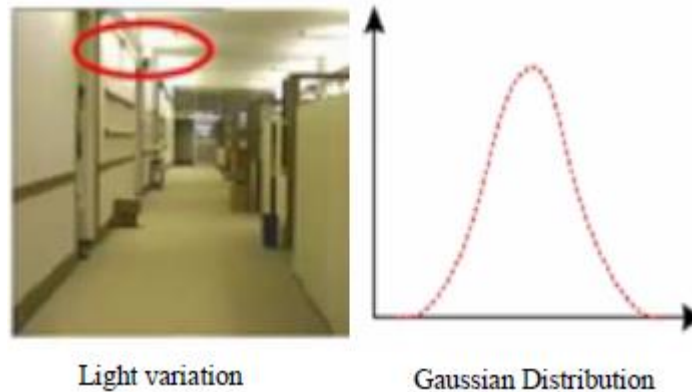


Figure 3: Single gaussian background modelling

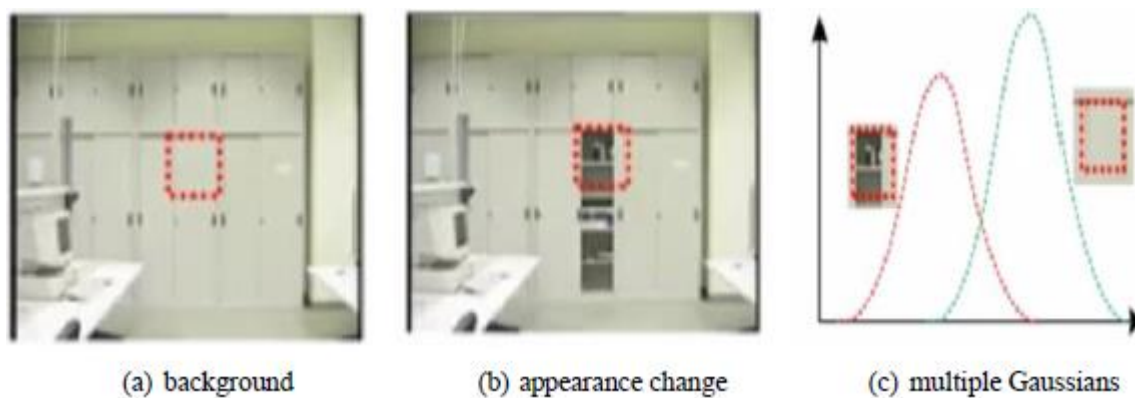


Figure 4: Mixture of gaussian background modelling

The Eq-4.1 is illustrate the Gaussian distribution

$$\eta(x; \mu, \sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2} \frac{(x-\mu)^2}{\sigma^2}} \quad (1)$$

Where, μ : mean vector, σ : standard deviation, and σ^2 : variance

$$\sigma = \sqrt{\frac{\sum (x-\mu)^2}{n}} \quad (2)$$

The mixture of gaussian (MoG)/ gaussian mixture model (GMM) is defined as expressed by Eq-3. The MoG/GMM is a mixture of K gaussians which describe the distribution of random variable x, as shown in figure 4.3.

$$\Pr(x) = \sum_{k=1}^K w_k \times \eta(x; \mu_k, \sigma_k) \quad (3)$$

$$\sum_{k=1}^K \omega_k = 1 \quad (4)$$

Where,

w_k =weight of k th gaussian

$\eta k(x;\mu,\sigma)$ = k th gaussian distribution

The proposed method is divided into foreground detection, shadow detection, shadow removal, and shadow-free foreground tracking. In the proposed method the foreground detection is from a Mixture of Gaussian for appearance change occur in the scene. The shadow detection, shadow removal, and shadow-free moving foreground tracking steps are the same as the proposed method of the chapter. The block diagram of the proposed method based on the mixture of Gaussian is illustrated in Fig.5.

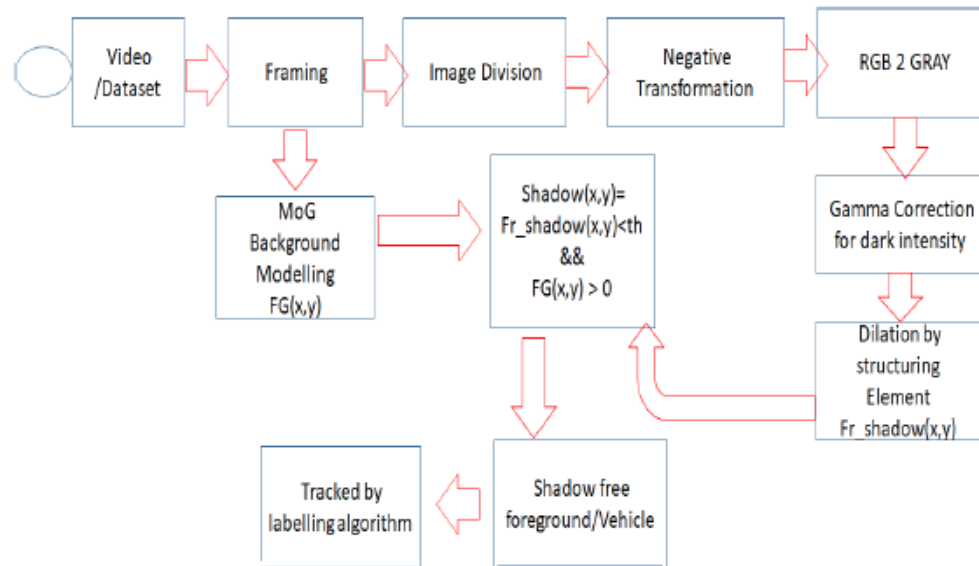


Figure 5: Method based on mixture of Gaussian

IV. RESULT AND ANALYSIS

The visual outcomes of these techniques in controlled conditions are shown in Figure 2. The approach suggested by [15-16] overly relights shadow areas. When compared to previous methods, our method and [17-18] offer results that are less impacted by shadow boundaries.

This work following figure 6 to figure 14, Illustration of the proposed scheme, firstly select image then it compute the shadow removed image.

1. Select the input image

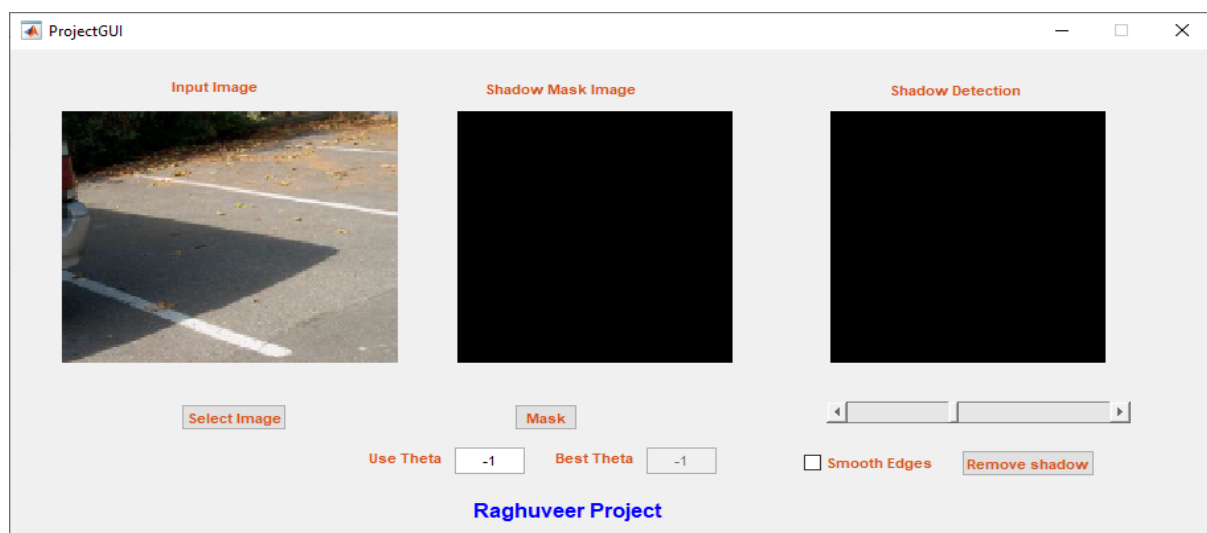


Figure 6:Original Starting Image

Figure 6 shows as original input image.

2. Shadow mask image

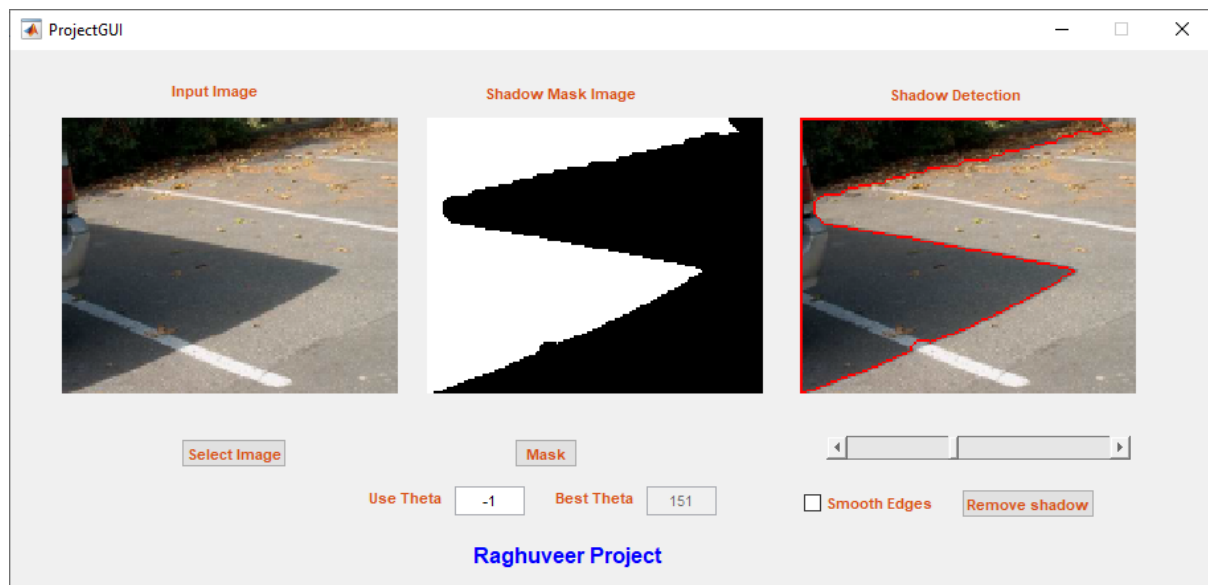


Figure 7: Masked Image

Click on mask to get the shadow mask image of input image and the shadow will be detected based on mask image.

3. Remove Shadow from input Image



Figure 8: Shadow removed Image

Similarly more number of experiments have been done for different input images and have been depicted below,

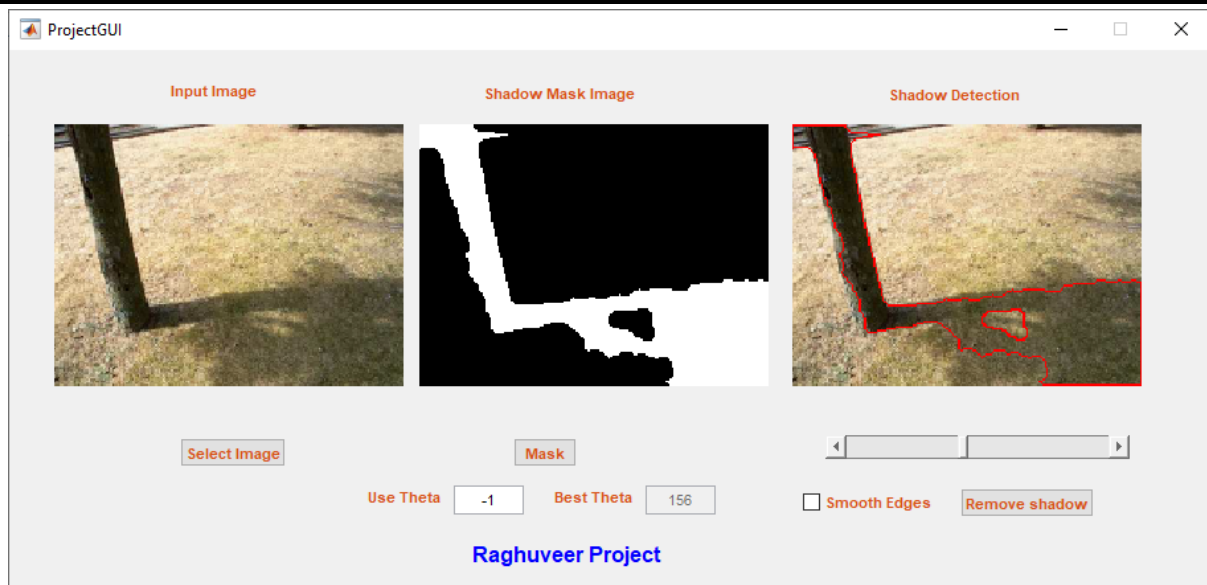


Figure 9: Masked Image



Figure 10: Shadow removed Image

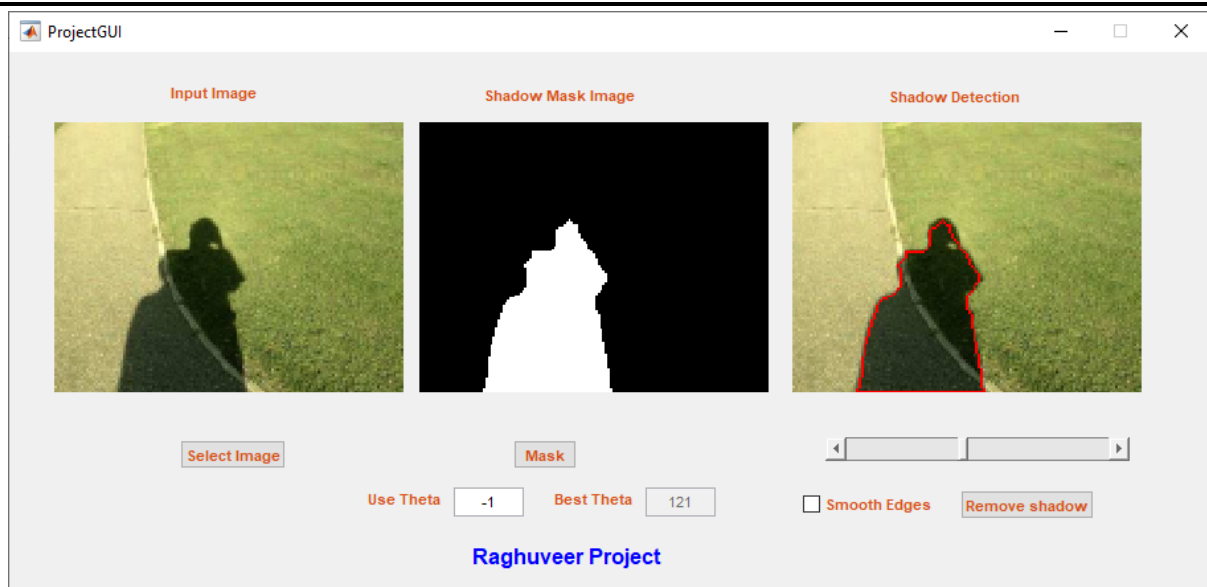


Figure 11: Masked Image



Figure 12: Shadow removed Image

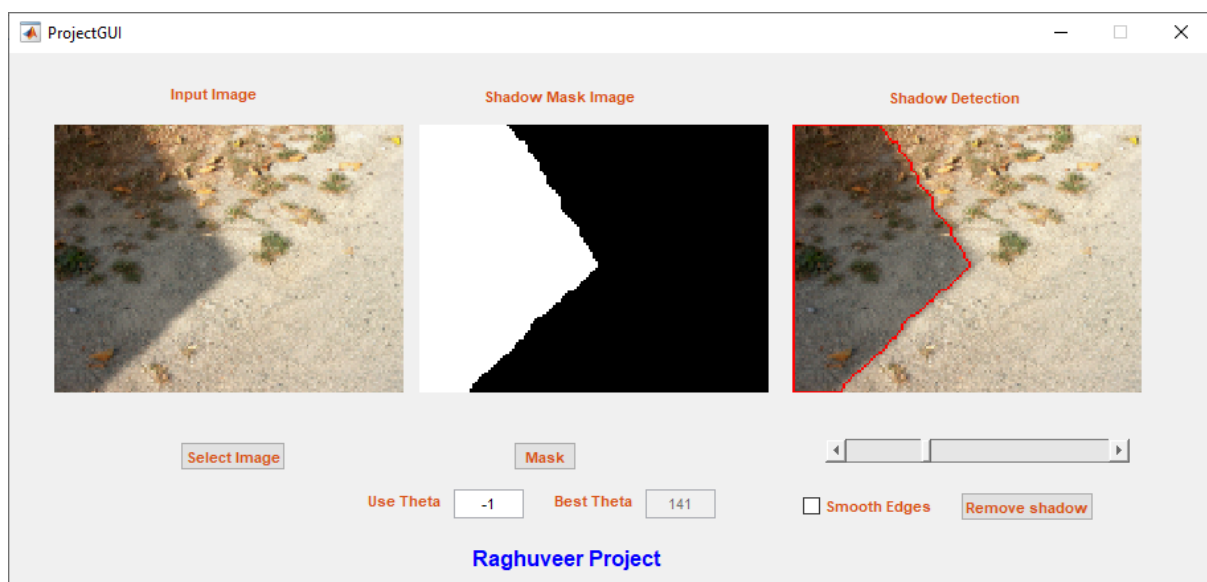


Figure 13: Masked Image



Figure 14: Shadow removed Image

The above experiments on different images have been done and the shadow removed images are obtained.

V. CONCLUSION

Images may contain shadows. Shadows can provide important information. They offer knowledge about surface geometry and spatial organization. Algorithms for segmenting images suffer significant harm when shadows are present. For object tracking algorithms like those used to monitor vehicles and humans, shadows can be very confusing. The main objective of the suggested approach is to produce a shadow-free image while maintaining the image's original information. Intensity of Shadow, Umbra and Penumbra, Light Source, Scene Characteristics, Self-Shadows and Shading, Complexity of Shadowed Surface, Geometry of the Shadowed Surface, Intersection of Shadow and Reflectance Boundaries are some of the issues and challenges of shadow removal that are highlighted in this study and their solutions are provided.

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