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A REFLECTANCE-BASED METHOD FOR SHADOW DETECTION AND REMOVAL IN VIDEOS

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ABSTRACT

Shadows are ubiquitous. They are formed when light is partially or fully occluded by objects. Shadows provide information about lighting direction, scene geometry and scene understanding in images and are crucial for tracking objects in videos. They alsoform an integral part of aerial images. However, shadows can also complicate tasks such as object detection, feature extraction and scene parsing. There have been many methods proposed to detect shadows from images and videos. In this paper we focus on detecting shadows from color images. With the recent boomin data driven approaches, machine learning based methods havebeen applied to detect shadows. In Conditional Random Fields consisting of 2490 parameters are used to detect shadows in gray scale images using features such as intensity, skewness, texture, gradient similarity etc. Our goal is to group different regions of an image based on their reflectance, texture and illumination characteristics. To group pixels with similar properties into different regions, we first segment an image using the Quickshift method with a Gaussian kernelsize of 9. Our assumption is that a single segment should contain pixels with similar reflectance and illumination. In this project we group different regions of an image based on their reflectance, texture and illumination characteristics. To group pixels with similar properties into different regions, we first segment an image using the Quick shift method with a Gaussian kernel size of 9. Our assumption is that a single segment should contain pixels with similar reflectance and illumination. An example of segmentation result is shown in Figure above. In the subsections we explain how we design the reflectance, texture and illumination classifiers to label each segment as shadow or non-shadow.

I. INTRODUCTION

1.1 Shadow

A shadow is an area where direct light from a light source cannot reach due to obstruction by an object. There have been few studies concerning shadow removal, and the existing approaches cannot perfectly restore the original background patterns after removing the shadows. The patterns of shadow rely on size of objects and the angles of lighting source. This may lead to problems in scene understanding, object segmentation, tracking and recognition. Because of the undesirable effects of shadows on image analysis, much attention is paid to the area of shadow removal over the past decades and covered many specific applications such as traffic surveillance, face recognition, image segmentation and so on . There are disadvantages like loss of

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information for the surface under the shadows present difficulties for image interpretation, image matching, detection and other applications. There are a number of cues which suggest the presence of shadows in a visual scene and that are exploited for their detection in digital images and image sequences . Shadow removal from respective image can be used for object detection, such as cancer detection, military object detection etc., as sometimes images are covered by shadows. After removing these shadows, objects in the images will appear more obviously so that they are recognized correctly. The algorithm used to remove the shadow is shown in it. The first step is to load image with shadow, which have probably same texture throughout. Remove pepper and salt noise by applying contra harmonic filter. To remove shadow properly, average frame is computed to determine effect of shadow in each of the three dimensions of colour. So the colours in shadow regions have larger value than the average, while colours in non-shadow regions have smaller value than the average values. Images are represented by varying degrees of red, green, and blue (RGB). Red, green, and blue backgrounds are chosen because these are the colors whose intensities, relative and absolute, are represented by positive integers up to 255. Then, construct a threshold piecewise function to extract shadow regions. 2 Satellite and aerial imaging is a common method to obtain information about objects on the Earth's surface. Object and target detection is of great interest for many applications, including rescue operations and defense applications. Recently, the object detection to man-made structure detection in aerial images has attracted. The ability to detect structures helps in understanding the scene contents of the image and may be used for content-based retrieval in databases and in other applications such as residential development planning, damage condition, and military target detection application. The shadow is detecting the existence of the buildings and other man-made structures in the overhead images. Shadow of buildings is isolated and then is employed for detection by integrating and fusing the geometry of the shadow area with the potential geometry of the building or other elevated man-made structures. In the colour imagery, the primary cue for shadow detection is the colour in addition to the texture feature of the image contents. In the multi spectral imagery, the characteristics of the bands are the main source of the information for shadow detection. The patterns of shadow rely on size of objects and the angles of lighting source. This raising the problem in scene understanding, object extraction, tracking. Because of the effects of shadows on image analysis, much attention is paid to the area of shadow removal over the past decades and covered many specific applications such as traffic surveillance, image segmentation and so on. There are disadvantages like loss of information for the surface under the shadows present difficulties for image interpretation, image filling, detection and other applications. There are a number suggest the presence of shadows in a visual scene and that are exploited for their detection in digital images and image sequence.

1.2 Shadow Removal

Shadow removal from respective image can be used for object detection, such as cancer detection, military object detection etc., as sometimes images are covered by shadows. Then removing these shadows in the image, objects in the images will appear more obviously so that they are recognized correctly. In this reports we present a hypothesis test to done by the process of detect shadows from the images and then energy function is supplying the more light to remove the 3 shadow from the image. The general advantages and wide applications of the shadow removal (contra harmonic filter, RGB colour model, hypothesis test, energy function) using detection of man-made structures in satellite image . However, information and prior shape and size information of the shadows are not there in the images. The shadow region change during the day based on the position of the sun and the sky fall on the structures that generate the shadow areas. In the algorithm the added the RGB image loaded from the shadow and salt and pepper noise is removed from the contra harmonic filter and average colour is computed and the shadow can detected by using binary and morphological process. And next process done by energy function is supply. A method to detect and remove shadows from a single RGB image is proposed. A shadow detection method is selected on the basis of the mean values of A and B channels of the LAB image. The shadow removal is done by multiplying the shadow regions by a constant. Finally the shadow edge is corrected by using filters. The shadow removal technique proposed in this report gives fast results and does not need multiple images or camera calibration. A problem with this approach is that the dark objects are misclassified as shadow areas. The performance can be improved further by employing region-based techniques as in to recover the shadow region. In city levels, floor scenes are clearly difficult, with a superb mixed bag of items and shadows framed by using raised questions, as an example, excessive systems, scaffolds, and trees. Despite the fact that shadows themselves may be viewed as a kind of valuable statistics in 3-D reclamation, building location acknowledgment, and tallness estimation they could likewise meddle with the preparing and use of high-dedication faraway detecting snap shots. IKONOS, Quick Bird, Geo Eye, and Resource three for the perception of Earth and the fast development of a few airy levels, for instance, aerial shuttles and unmanned flying cars, there has been an increasing need to look at highdetermination pictures for exceptional packages. Case in factor, shadows might also result in ill-advised outcomes amid exchange identity. 4 Likewise, the recognition and evacuation of shadows assume an imperative component in usage of city high determination far flung sensing images. In the ultimate ten or extra years, with the supply of high spatial decision satellites which include IKONOS, Quick Bird, GeoEye, and Resource three for the remark of Earth and the speedy improvement of someaerial structures inclusive of airships and unmanned aerial cars, there has been an growing want to investigate high-decision pictures for unique packages. In urban regions, floor functions are quite complicated, with a brilliant variety of gadgets and shadows shaped via multiplied items along with high buildings, bridges, and timber. Although shadows themselves may be seemed as a kind of useful information in3-D reconstruction, building function popularity, and peak estimation they also can intervene with the processing and alertness of highresolution for flung sensing images. For instance, shadows can also reason wrong effects at some point of trade detection. Consequently, the detection and removal of shadows play a crucial function in packages of urban high resolution remote sensing snap shots consisting of object classification, object recognition, exchange detection, and photo fusion. Many effective algorithms were proposed for shadow detection.

II. LITERATURE SURVEY:

In some applications, especially traffic analysis and surveillance system , the existence of shadows may cause serious problems while segmenting and tracking objects: shadows can cause object merging. For this reason, shadow detection is applied to locate the shadow regions and distinguish shadows from foreground objects. In some cases, shadow detection is also exploited to infer geometric properties of the objects causing the shadow ("shape from shadow" approaches). In spite of the different purposes, invariably the algorithms are the same and can extend to any of these applications. A. Prati et al conducted a survey on detecting moving shadows; algorithms dealing with shadows are classified in a two-layer taxonomy by the authors and four representative algorithms are described in detail. The first layer classification considers whether the decision process introduces and exploits uncertainty. Deterministic approaches use an on/off decision process, whereas statistical approaches use probabilistic functions to describe the class membership. As the parameter selection is a crucial problem for statistical methods, the authors further divided statistical methods into parametric and nonparametric methods. For deterministic approaches, algorithms are classified by whether or not the decision can be supported by modelbased knowledge. The authors reviewed four representative methods for there categories of his taxonomy and argued that Deterministic Modelbased methods rely so much on models of the scene that they inevitably become too complex and time-consuming. T. Horprasert et al'smethod is an example of the statistical nonparametric approach and the authors denote it with symbol SNP. This approach exploits color information and uses a trained classify to distinguish between object and shadows. I. Mikic et al proposed a statistical parametric approach (SP) and utilized both spatial and local features, which improved the detection performance by imposing spatial constraints. R. Cucchiara et al's method (DNM1) and J. Stauder et al'swork (DNM2) were representatives of deterministic non-model based method. 27 DNM1 is based on an assumption that shadows in image do not change the hue of surfaces. The reason why the author reviewed DNM2 is that it is the only work that handles the penumbra regions in image. The survey of A. Prati et al mainly focuses on the moving shadow detection and most of the papers they reviewed do not examine the self-shadow and typically they concentrate the attention on umbra, considering the penumbra as a particular case of umbra. It is because the distance between the objects and the background is

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negligible compared to the distance of illumination sources to the objects in a highway scene and most or all of the shadows are umbra or strong shadow. S. Nadimi and B. Bhanu proposed physical model based method to detect moving shadows in video. They used a multistage approach where each stage of the algorithm removes moving object pixels with knowledge of physical models. Input video frame is passed through the system consists of a moving object detection stage followed by a series of classifies, which distinguish object pixels from shadow pixels and remove them in the candidate shadow mask. At the end of the last stage, moving shadow mask as well as moving object mask is obtained. Experimental results demonstrated that their approach is robust to widely different background surface, foreground materials and illumination conditions. E. Salvador et al proposed an approach to detect and classify shadows for still images . They exploit invariant color features to classify cast and self shadows. In the first level, the authors utilize edge detection followed by a morphological operation to extract object and cast shadow regions.

III. EXISTING METHODOLOGY:

3.1.1Simple shadow removal

Given the location of shadows, how can we obtain highquality shadow-free images? Several methods have been proposed so far, but they either introduce artifacts or can be difficult to implement. It was proposed that a simple method that results in virtually error and shadow-free images in a very short time. Our approach is based on the insight that shadow regions differ from their shadow-free counterparts by a single scaling factor. It derived a robust method to obtain that factor which shows that for complex scenes -containing many disjointed shadow regions- our new method is faster and more robust than others previously published. The method delivers good performance on a variety of outdoor images.

3.1.2 Introduction The presence of strong illumination variations in an image, shadows in particular, have been shown to be problematic for a variety of computer vision algorithms. Tracking , scene analysis and object recognition are all examples of problems where a single illuminant is desirable. In most real-world applications, shadows are the main example of such variations. Shadows are cast in an image when an object lies in the way of the main illuminant. Whether due to the scene geometry -fixed objects such as buildings- or the conditions under which the image is taken -such as using a flash-, the presence of shadows can not always be prevented. In conventional photography, and with the advent of cameras able to capture more than 8 bits per channel, strong shadows also often characterize a high dynamic range (HDR) image. HDR images cannot always be properly displayed on current monitors. If one can remove or attenuate shadows in the image, the dynamic range can be reduced and the image displayed. In recent years, several methods have been proposed to remove shadows from images. All of them require shadows to be identified first. The first group of methods is based on image sequences; in a sequence of outdoor images taken from the

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same viewpoint, the major differences between images are due to illumination variations. This idea, explained in it, enables to obtain invariant -independent of the illuminant- images and remove shadows from surveillance camera images.

3.2 Shadow Detection

Prior to removing shadows, we first need to detect them. To this effect, we use the invariant image method proposed in with the additional "closed region" constraint developed . Invariant -that is, reflectance only- images are first obtained by projecting the image log-chromaticities in the entropy minimizing direction. Edge detection is performed on both the original and the invariant image, the difference of the two edge maps is used to identify shadow edges. Finally, the shadow edges are completed since shadow regions are closed regions. An illustration of the process is shown in Figure 1, we refer the reader for more details about the procedure.

3.3 Shadow Removal

shadows can be removed from images with two insights. Firstly, if 2 pixels on both sides of the shadow edge have the same reflectance, then they should have the same value once the shadow is removed, i.e. their gradient should be equal to 0. Secondly, within the shadow regions, log ratios between pixels are preserved when the shadow is removed; this assumption being in line with most lightness algorithms. It is thereafter assumed that all images are first transformed to the log domain and then exponentiated when the shadows have been removed. Shadow-free images can therefore be obtained by taking the derivatives of the original image, setting the shadow edges derivatives to 0 and finally reintegrating the image. Two different methods for reintegrating shadow-free images have recently been proposed. One reintegrates the image by solving a Poisson equation, a 2-dimensional method. The other method uses random Hamiltonian paths and 1-dimensional integration . Some results obtained with our method can be seen . Despite the complexity of some of the scenes, the shadows are correctly removed or attenuated. The luminance levels 33 on both sides of the (former) shadow are almost identical and the color balance is adequate. One of the main advantages of this method, though, is its speed. Indeed, given the shadow edges, the problem is reduced to finding a constant under 2 simple constraints. Such a task can easily be done in real time (even in MATLABtm). In contrast, the 2D reintegration method requires inverse Fourier transforms that are 4 times the size of the image and the 1D method needs several different Hamiltonian paths per shadow region. The proposed method is a simple, fast and efficient way to remove shadows from images once the location of shadows has been found. We show that the shadow removal problem can be reduced to finding a constant at the "smoothest" locations of the shadow edge under simple constraints. The results show that this method outputs high quality images where the shadows are either removed or strongly attenuated. In case of indoor images, or of shadows created by other illuminants, one could theoretically extend the proposed framework by, for example, further constraining the behavior of the constant if required in a specific experimental setup.

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3.4 Shadow Detection and Removal for Traffic Images

Shadow detection and removal in various real life scenarios including surveillance system, indoor out door scenes, and computer vision system remained a challenging task. Shadow in traffic surveillance system may misclassify the actual object, reducing the system performance. There are many algorithms and methods that help to detect a shadow in image and remove such shadow from that image. This report is aimed to provide a survey on various algorithms and methods of shadow detection and removal with their advantages and disadvantages. This report will serve as a quick reference for the researchers working in same field.

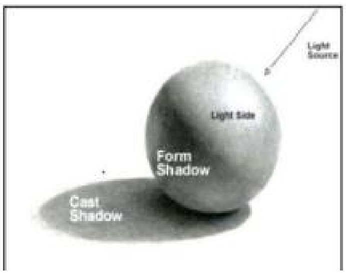

Figure 4.1 Shadows can be Broadly Divided into Cast and SelfShadow

3.5 TVQI

We present a new algorithm for illumination normalization and uneven background correction in images, utilizing the recently proposed TV+L1 model: minimizing the total variation of the output cartoon while subject to an L1- norm fidelity term. We give intuitive proofs of its main advantages, including the well-known edge preserving capability, minimal signal distortion, and scale-dependent but intensity-independent foreground extraction. We then propose a novel TV-based quotient image model (TVQI) for illumination normalization, an important preprocessing for face recognition under different lighting conditions. Using this model, we achieve 100% face recognition rate on Yale face database B if the reference images are under good lighting condition and 99.45% if not. These results, compared to the average 65% recognition rate of the quotient image model and the average 95% recognition rate of the more recent self quotient image model, show a clear improvement. In addition, this model requires no training data, no assumption on the light source, and no alignment between different images for illumination normalization. We also present the results of the related applications - uneven background correction for cDNA microarray films and digital microscope images. We believe the proposed works can serve important roles in the related fields.

IV.PROPOSED METHODOLOGY:

4.1 Shadow Removal :

In this work, we automatically detect and remove distracting shadows from photographs of documents and other text-based items. Documents typically have a constant colored background; based on this observation, we propose a technique to estimate background and text color in local image blocks. We match these local background color estimates to a global reference to generate a shadow map. Correcting the image with this shadow map produces the final unshadowed output. We demonstrate that our algorithm is robust and produces highquality results, qualitatively and quantitatively, in both controlled and real-world settings containing large regions of significant shadow. Images of documents, receipts, menus, books, newspapers, flyers, signs, and other text are frequently captured. Whether we are sending a page from a textbook highlighting important information, taking a picture of an ancient engraving while on vacation, or just saving an illustration from a loved one, such images show up in our everyday lives. However, these images are highly susceptible to shadows due to occlusions of ambient light by the photographer or other objects in the environment. These shadows cause distracting artifacts that can make an image difficult to interpret or use. In this report, we propose an automatic technique to detect and remove shadows from images of documents. Our main observation is that documents typically have a constant colored background; for example, the actual color of the paper typically does not change throughout a document. However, illumination effects like shadows and shading cause changes in observed images intensities. Our technique detects these changes and enforces a consistent background color to produce the unshadowed output. In particular, we estimate text and background colors in local blocks of the image and generate a shadow map that uses a per-pixel gain to match these local background estimates to a global reference. We evaluate the robustness of our approach, both quantitatively and qualitatively, on a variety of controlled and real-world examples. There are two main categories of work in shadow removal. The first category focuses on removing shadows from general images, such as typical outdoor pictures, that have strong distracting shadows. For example, Guo et al.remove shadows from natural images by finding corresponding shadow and non-shadow regions and performing a per-pixel relighting. Lastly, there are algorithms that use shadow estimation for a specific application such as video relighting orshape recovery . All these methods tend to have artifacts when applied to document images. A second category of techniques has been specifically developed to remove shadows from document images. Some such methods , inspired by general intrinsic approaches, correct geometric distortions and can estimate illumination within their framework to address shading artifacts. Our approach is more similar to the state-of-the-art method of Oliveira et al. , where a constant color for the document background is assumed to generate a gain map. However, they detect background-only regions and interpolate the remaining areas of the gain map. Therefore, their method can fail to remove shadows when excessive interpolation is required to fill in the holes of the gain map. Our approach, on the other hand, can effectively estimate the gain map in text and background regions, so it does not suffer from interpolation inaccuracies. Finally, Adobe Acrobat uses an “Enhance” feature on images of documents that is typically used to brighten dark images. However, since this applies a global correction, it fails to remove local shadow regions and leaves residual shadows. Our approach performs analysis on small overlapping blocks throughout the document and is thus able to correct localized shadows. Finally, there are image binarization methods that segment an image into black and white and discard all colorinformation . We note that, although related to our work, these approaches have the fundamentally different goal of creating a binary image that is more effective for optical character recognition (OCR) applications. On the other hand, we aim to improve documents by removing their shadows while still keeping the same color and tone as the original. Thus, we view this field of work as orthogonal to ours. In fact, we demonstrate how our method can be used as a pre-process to improve binarization techniques and thus the OCR applications that use them. Our main observation is that documents tend to have a constant colored background throughout, so the unshadowed output should have this property as well. We propose to apply a factor, αi , as determined by our computed shadow map

4.2 Computing Shadow Map

We expect the global background color to be the true background color. The local background color deviates from this because of illumination effects such as shadows and shading. In order to remove the influence of illumination, we compute the ratio of the local and global background colors to generate the shadow map as: where `i is the local background intensity at pixel i and g is the global background reference for all the pixels. Moreover, αi maps each input pixel to the reference background color and, when applied to the input image (Eq. 1), produces the final unshadowed result.

4. 3 Implementation Details

We implemented our algorithm in C++ and it takes roughly 2 seconds to process a 1024×1024 image, with clustering being the most costly sub-process. Thus, for acceleration, we randomly sample 150 pixels in each block (21 × 21) for local clustering and 1000 pixels throughout the entire image for global clustering. For further speed-up, we do not perform local clustering at each pixel. Instead, we only consider pixels at specific strides (i.e., 20 in our implementation) for calculating the local background intensities. Thus, our shadow map is stride times smaller than the input image. To get the full resolution shadow map, we upsample using an 8 × 8 Lanczos filter. Note that since we use a stride, the low resolution shadow map can have some slight noise due to differences in cluster means, so we first apply a 3 × 3 median filter followed by a Gaussian filter (σ = 2.5) to smooth it out and avoid small blotchy artifacts in the final result. Since illumination tends to vary smoothly and generates soft shadows in practice, computing a downsampled shadow map does not adversely affect our results. Finally, text can have a lot of variation in intensity values and two clusters is not always sufficient to capture accurate statistics. Thus, we found that using three means for both the local and global clustering worked

4.4 RGB COLOR MODEL

The red, yellow, and blue (RYB) primary colors became the foundation of color theories that described how artists mixed paint pigments to produce colors. These theories were summarized by Johann Wolfgang von Goethe (the famous German poet) in his document the Theory of Colors, published in 1810. In the late 19th century, German and English scientists established that a color model based on red, green, and blue (RGB) was better for describing human color perception because the cones in the human retina responded to these colors of light.

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The RGB color model is described below. 40 The RYB Color Model is a subtractive system. A mixture of two primary colors is darker than the original colors. A mixture of all three primary colors should approximate black, although this is usually not precisely true. A popular theory in Europe during the late 18th century was that the harmony of a painting required colors with equal saturation. Bright red and blue colors existed (for example carmine and ultramarine), but no equally bright yellow. This motived a large effort among chemists to develop a good yellow pigment. Although the secondary colors orange and green can be created by mixing primary colors (orange = red + yellow and green = yellow + blue), the resulting colors are darker than the original primary colors; it is better to use orange and green pigments directly. The RGB color model was first described by Thomas Young and Herman Helmholtz in their Theory of Trichromatic Color vision (first half of the 19th century) and by James Maxwell's color triangle. In addition to providing a good description of human color perception, the RGB model is the basis for displaying colors in television and computer screens. The RGB model is also used for recording colors in digital cameras, including still image and video cameras. The RGB model is an additive system. In practice, the RGB model must be modified to account for the characteristics of each device. In many cases, the response of visual recording devices is nonlinear, which require some sort of gamma correction. To represent colors for a television or computer screen, each pixel of the screen is recorded as the triple (r,g,b) of numbers. One popular system uses numbers that range from 0 to 255 for each color. RGB primaries are additive:

- Main diagonal =>gray levels
- black is (0, 0, 0)
- white is (1, 1, 1) 41 Hue is defined by the one or two largest parameters
- Saturation can be controlled by varying the collective minimum value of R, G and B
- Luminance can be controlled by varying magnitudes while keeping ratios constant.

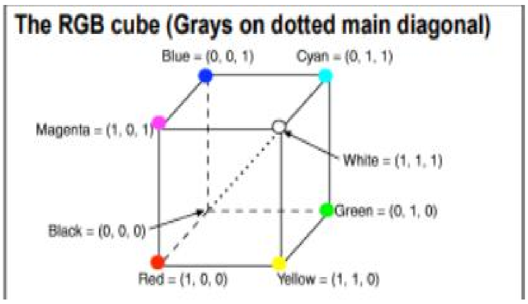

Figure 4.1 The RGB cube

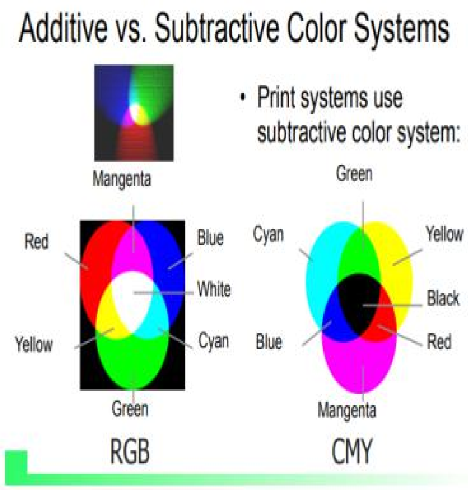

Figure 4.2 Additive vs Subtractive color systems

A statistical hypothesis is an assertion or conjecture concerning one or more populations. To prove that a hypothesis is true, or false, with absolute certainty, we would need absolute knowledge. That is, we would have to examine the entire population. Instead, hypothesis testing concerns on how to use a random sample to judge if it is evidence that supports or not the hypothesis.

V.RESULT:

The result of the shadow removal, the corresponding colour shadow pixels and removed. In first process we done by pre-processing and segmentation in the image by using contra harmonic filter the pepper noise is removed in the image. In the binary technique convert the normal image to salt and pepper image. Next process of the average colour pixel value of RGB primary colours component in the image are consider by dark pixel of shadow region. Then hypothesis test is used to detect the shadow in the image and the detected shadows are comparing average values of primary colour component with original values of primary colour in the image. And then shadow removal done by using energy function. The shadow pixels that belong to a corresponding colour are isolated and removed. In this work first preprocessing of image/videos is done by filtering the image using filter's where pepper noise is removed. Then, average colour values of red, green¸ blue (primary) components in image are obtained which are considered dark pixels as of shadow regions.

VI.CONCLUSION:

In the reports we produce the methods of remove shadow for coloured backgrounds. This algorithm removes the large amount of shaded colours pixels and added same colour background pixels without losing the present data's using the MatLab software. This final image (Shadow enhanced image) used for target application and various applications. we have presented a novel framework for shadow removal in single images. Our main contribution is to use deep networks as the parameters estimators for an illumination model. Our approach has advantages over previous approaches. Comparing to the traditional methods using an illumination model for removing shadows, our deep networks can estimate the parameters for the model from a single image accurately and automatically.

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