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# Shadow removal using texture and color clustering

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**ABSTRACT**

While perfect illumination conditions are not usually available at most of the vision sites the resulting shadows are in role of poison for countless algorithms and applications, despite the numerous efforts which have been put yet most of the presented solutions have major disadvantages, at this work a method with mediocre computation load and high reliability is presented which abolishes the soft shadows with respect to the texture and color clusters without attending to detect the shadowed regions.

**KEYWORDS**
shadow removal, texture and color analysis, computer vision.

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## Introduction

Since perfect lighting situation is not always guaranteed for the work scenes the lack of proper illumination causes some areas to seem darker which has always been assumed as a troublesome event (Gershon et al., 1986). The shadows can be categorized based upon the darkness level to soft and hard shadows (Saritha, 2013). At soft shadows the intensity degradation is about low so the background texture and colors are intact while the hard shadows are extremely veiled so that little or no textures are preserved. The hard shadows are not recoverable because no kind of illumination and equalization will restore the texture and

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abolished data so all the efforts are about to normalize the soft shadows where recoverable data exists.

With respect to the enlightening direction over the presented objects at the scene there is another possible categorization of the shadows. The self-shadow and cast shadow (Jyothisree and Smitha, 2013). The self-shadow is actually the dark side of the object which is not illuminated by the light source while the cast shadow is the background area which is deprived from the light beams because of the obstacles.

While the hard shadows usually have detectable and sharp edges the soft shadows often come with projected light degradation slops and perspective depended on the unpredictable scene conditions like the light source intensity, object locations and reflections (Jyothisree and Smitha, 2013). Thus edge detection is not a favorable option to detect and recognize anything where shadows are presented at the frame. Also shadow detection methods which use edge detection as a part of the operation are dismissed (Jain et al., 1995).

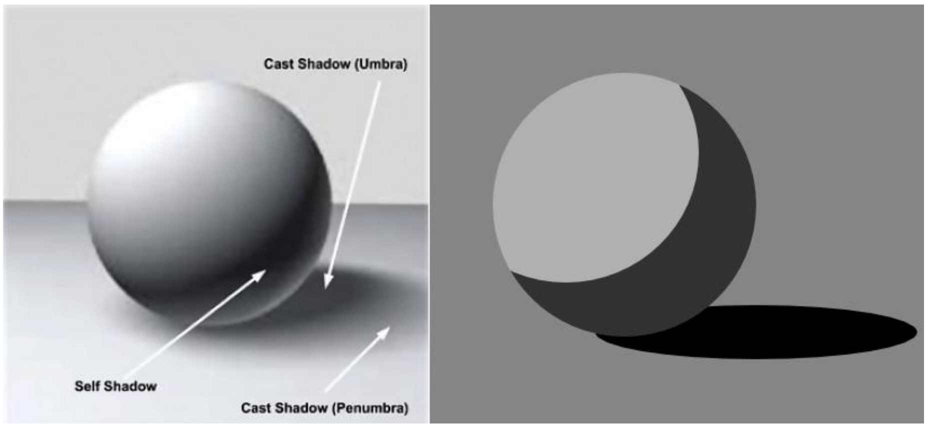


**Figure 1-a, b**: self and cast shadows can be corrected with simple normalization filtering to comprise sharp edges but this will definitely jeopardize any object detection method based on edges and also the normalization factors and filtering parameters must vary in response to the unforeseen lighting and reflection conditions.

Shadows deliver major discriminations to nearly all machine vision application (Jiang and Drew, 2003). They can easily disrupt Tracking, scene analysis and object recognition because lighting and reflection conditions are not always predictable. Its while nearly all of the previously invented algorithms and methods to resolve this are highly depended on particular and restricted lighting intensity, radiation angle, object position and reflection grades and thus not utilizable for practical applications (Jiang and Drew, 2003).

## Previous works

Since the need for illuminating invariant images is certainly essential and serious there had been quite a number of tries so far. The task of abolishing shadows is either accomplished through the two stages of detecting the shadowed area and correcting the illumination level at those or at some cases removing each pixel of shade without an attempt to determine the shadowed area at first. Over all the entire prior represented works can be classified as the following categories:

### methods which work upon comparing the illumination properties of a same scene at multiple images.

Like in (Klinker et al., 1990) where Weiss has taken a strategy of capturing multiple images from a singular scene under different illumination conditions or a more comprehensive but similar work at (Klinker et al., 1990) while both require a steady camera and constant scene with some restrictions on the reflecting surfaces types. Another example is presented at which requires a shadow less original image. There have been even some attempts to anticipate the position of the cast shadows with respect to the day light properties of the specific date. No doubts that such methods can't be utilized when motion is applied to either the camera or the scene even if the mathematical or logical approaches were reasonable.

### Methods which use single image but human operator interaction.

Like in (Swain & Ballard, 1991) where user is supposed to distinct on the shadowed area he determines on the images or in (Klinker et al., 1990where user is supposed to provide visual hints for the devised energy minimization algorithm. Another example is presented in (Jiang and Drew, 2003) where user should approve the separated texture regions which may have been partly shaded. No need to remind that user interaction is not available nor possible at the over whelming majority of the presumed applications.

### Automated methods requiring a single image.

As the main topic of discussion such an approach has been the most contributed one. Some may be rather simple while others have used complicated mathematics and conversions of images. For example at (Jiang and Drew, 2003) the authors assumed that if the RGB space gets alternated with the LAB the shadowed areas may only vary in the L component (illumination) and not in A or B color spaces. At (Jiang and Drew, 2003) the same concept is utilized under a different title. Some others have used more sophisticated methods, for example in (Weiss, 2001) Finlayson has assumed that shadowed segments have always edges orthogonal to the direction of illumination gradients. However obviously the effect of multiple light sources and reflections could easily compromise this perception. Actually such a solution had been debunked long before this like in (Jiang and Drew, 2003).

In (Weiss, 2001) the authors have segmented the image and then compared the color features of the segments to decide if the inspected one is a shadowed area or not, it's actually another attempt like in (Gershon et al., 1986) in addition of considering the directions of the illumination gradients like in (Jiang and Drew, 2003) but both are barely robust and vulnerable to ambient changes.

More complex methods are authored in (Gershon et al., 1986) where some conversions are made upon the image matrix. Although different explanations are contributed at these two but they are fundamentally alike, first a 1D illumination properties map is generated based on the reflection features of different segments. Then a 2D map of color segments is generated without considering the illumination variances and then a 3D energy map is comprised named as intrinsic image and resurrected to achieve illumination invariant image. Though the approach may sound different but its just another cover for the simpler LAB analysis method mentioned above; in [21] the Wein reflecting model of surface is also utilized to enhance the method but it renders the job to be sensitive confronting the ambient modifications.

At the class there have been also strategies which don't consider the determining and separation of shadowed segments but attend to abolish the shade directly through some mathematic algorithms like TAM or histogram equalization in (Saritha, 2013) which actually reduces-induces the illumination level of the pixels which may lead to the loss of information like edges or textures. There had been some other methods which use the previously known 3D models of the presented objects at the scene like in (Jiang and Drew, 2003); even at [23,24] based on the introduced features of shadows decision making classifiers have been trained to determine if some segments are shadows or not but such trends are not to be argued here since we desire a rout to vanish the shade without requiring any prior knowledge or user interfaces hence it can be utilized for autonomous computer vision and robotic applications.

## Current work

To reach a better interpretation of shadow removal solution it would be a good idea to seek natural paradigms. Upon which features does our brain distinguish shadows and shades on its visual processing section? This concept had been a subject of research since behind a decade (Saritha, 2013), based on the research we do notice the shape, position, lighting direction, color, texture and amount of darkness applied to decide whether if a region is shaded or not but what definitely defines a shadow is the contemporary existence of applied darkness and brightness which preserved the texture and color of the area. But if a specific texture exists all consumed in the shadow still it's impossible to assume that the object has been accurately fit with the shadow and this can be mistaken with a dark colored object. In other words it's not true to associate the shadowed area with certain objects (Saritha, 2013).

So in order to prepare an illumination invariant image we devise our approach as follows, now that after color and texture clustering each pixel belongs to one color and one texture clusters we can calculate the average brightness at both groups, add them up and divide into two. Now if this yield is lower than the whole image's average brightness we assume the average brightness itself and again should the extracted outcome is too high or white. This approach both weakens the shade on self and cast image and also can be effective about color-texture clusters which are all shadowed.

In other words we recognize both the color and texture categorization of each pixel. At each cluster we find the average brightness level presented among the pixels. Now we have two possible level of brightness to be corrected into and we consider both. Although this approach may lead to the strengthening of some originally dark colored areas but we should notice that it's unlikely to have very close color spectrums put at different brightness. Especially where the texture matters too. This means that the originally dark objects will most likely remain at the same brightness but we added a condition about the lower brightness so the ultimate brightness may be altered to the image's average.

The LAB conversion is used in order to a more convenient brightness measure.

Immediate advantages of this method in respect to the previous ones can be listed as follows. First this solution is not exclusive for colored or gray level images; second we don't attend to discover and separate the shadowed region and directly abolish the shade. Also the image quality is minimally effected only at the darkened areas, dark objects don't get illuminated since their texture is uniquely darkened; every illumination intensity and gradient directions are acceptable. The only possible weakness spot is where the images are of such a gray and low quality which no specific textures are detectable but such photos are useless anyway.

Before we continue on the color and texture identification methods we should remind that we are not going to extract connected components here but the clusters of the pixels which share similar color and texture.

## Gabor texture filtering

In image processing, a Gabor filter, named after Dennis Gabor, is a linear filter used for edge detection. Frequency and orientation representations of Gabor filters are similar to those of the human visual system, and they have been found to be particularly appropriate for texture representation and discrimination. In the spatial domain, a 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave.

Simple cells in the visual cortex of mammalian brains can be modeled by Gabor functions (Saritha, 2013). Thus, image analysis with Gabor filters is thought to be similar to perception in the human visual system.

Its impulse response is defined by a sinusoidal wave (a plane wave for 2D Gabor filters) multiplied by a Gaussian function. Because of the multiplication-convolution property (Convolution theorem), the Fourier transform of a Gabor filter's impulse response is the convolution of the Fourier transform of the harmonic function and the Fourier transform of the Gaussian function. The filter has a real and an imaginary component representing orthogonal directions. The two components may be formed into a complex number or used individually.

In discrete 2D space of an image the Gabor filters can be modified as follows:

$$G_c[i,j] = Be^{-\frac{(i^2+j^2)}{2\sigma^2}} \cos(2\pi f(i\cos\theta + j\sin\theta))$$

$$G_s[i,j] = Ce^{-\frac{(i^2+j^2)}{2\sigma^2}} \sin(2\pi f(i\cos\theta + j\sin\theta))$$

Where i and j are the coordinates of a pixel, B and C are normalizing factors to be defined by the users, and other factors can be utilized for vision purposes like f can be interpreted as the frequency looked for at the image or Θ will determine the likely direction of the texture and the $\delta$ is responsible to the size of image sub regions being analyzed.

For this particular application we only want to extract high frequency repetitions representing resolvable textures comprised of small neighborhoods.

## Color segmentation

There is no particular color segmentation methods needed here; we only require finding similar RGB components across the whole image. Assuming that we are not after connected components but clusters of similarities all across the images.

So, for each pixel we can consider this grouping approach:

The α here devotes the color clustering precision and is not a prominent parameter to discuss, having smaller α spells a higher accuracy and also more computation effort.

## The experiment results

Although one may think that he has seen a much better illumination recovery results but the experiences approve that a total relief of the shade is merely impossible and can be achieved if the same scene without a shadow is framed.

The first case, as shown in fig.2 is a scene of grass and pave; the original image on the right (fig.2-a) shows a soft cast shadow and the regenerated image on the left proves that our method has kept the texture in acceptable quality. However it is not a surprise to see that the method fails to remove hard shadows where no colors or textures are detectable. Also the color of the pave cant be refined because at this particular spectrum which is nearly gray even a soft shadow causes the original color to be lost.

**Figure 2-a,b**: the soft cast shadow on the grass and pave and the regeneration result.

Now the same approach is assumed about a scene with both cast soft shadow with reflection and a limpid transparent liquid with a color which is again reflected (fig.3). as can be observed the method has both weakened the shade and maintained the reflection colors.

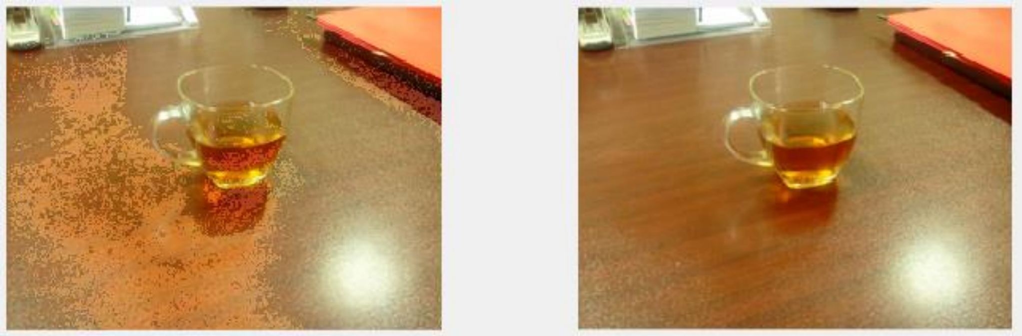

**Figure 3-a, b**: the method preserves the reflections.

Now lets discuss an image with barely distinguishable objects and single color (fig. 4), again the algorithm has been able to abolish both the self and cast soft shadows.

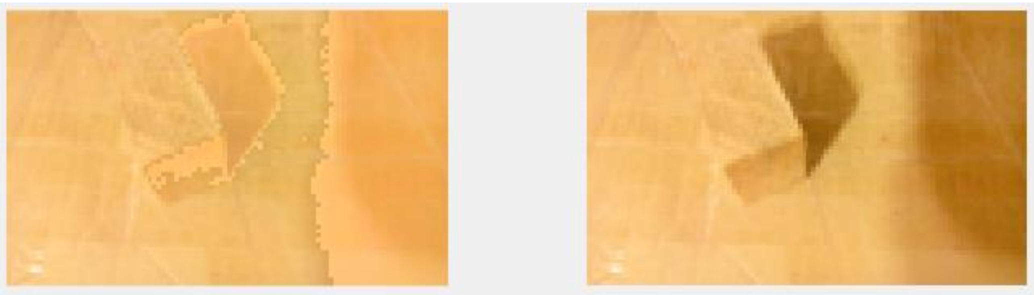

**Figure 4-a, b**: self and casted shadows at a monolithic object and back ground color.

Figure 5 indicates a nearly successful elimination of both self and cast shadows,

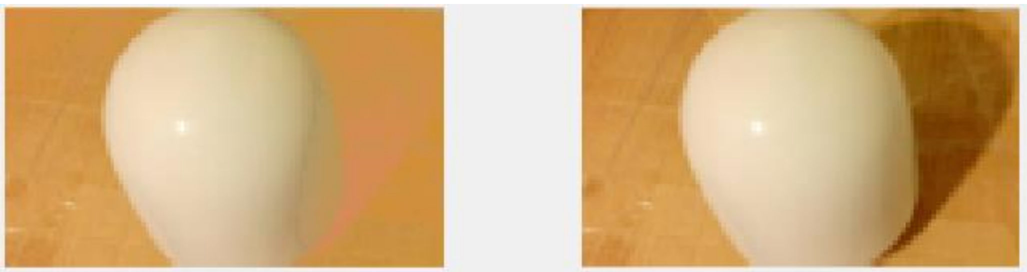

**Figure 5-a, b**: the soft shadows are almost completely eliminated.

Figure 6 is an example of the clustering method success where the flash reflection is not mixed with the close object hue because the texture intervenes too while even the lightest shadows are eliminated.

**Figure 6-a, b**: the texture clustering prevents the blend of similar hues.

Figure 7 shows that the same matter mentioned above remains effective at even closer hues.

**Figure 7-a, b**: the method both separates the most similar spectrums and reconstructs the colors of even lightest shadows.

## Conclusion

Although the method at some occasions only weakens the shadow and does not completely eliminates its influence yet again the recovered image can be put under the work again until desirable results emerge. As we can see the method has been applied directly on the color images, all shadows else than the hard ones are banished, similar hues are not mixed up, reflections and transparencies are intact, original dark colors are preserved and we don't attend to determine the shadowed pixels or any gradient- spatial analysis. Still two disadvantages can be assumed here, one that the mentioned texture detection pace requires some intensive computation efforts which slows the work but our algorithm is not restricted to utilize the Gabor filtering and any other approaches can be applied.

The other is that the texture is slightly affected but this is an unavoidable outcome of the tradeoff. In other words it's not possible to yield better results unless if the exact same scene is framed at better illumination conditions.

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## References

Gershon R., A.D. Jepson, , and J.K. Tsotsos. Ambient illumination and the de- termination of material changes. J. Opt. Soc. Am. A, 3:1700{1707, 1986.

Saritha Murali, "Shadow Detection and Removal from a Single Image Using LAB Color Space", NITC, Calicut, India, Cybernetics and information technologies, volume 13,No. 1, 2013.

Nasrin Hakim Mithila, "a Shadow Detection and Removal from a Single Image Using LAB Color Space", Chittagong University of Engineering and Technology, Bangladesh,IJCSI, Vol 10, Issue 4, No. 2, July 2013.

Jyothisree V. and Smitha Dharan, "SHADOW DETECTION USING TRICOLOR ATTENUATION MODEL ENHANCED WITH ADAPTIVE HISTOGRAM EQUALIZATION", College of Engineering Chengannur, Kerala, India, International Journal of Computer Science & Information Technology (IJCSIT) Vol 5, No 2, April 2013.

Jain R., R. Kasturi, and B. Schunck, Machine Vision. New York: McGraw-Hill, 1995.

Jiang H. and M. Drew. Tracking objects with shadows. In CME03: International Conference on Multimedia and Expo,, pages 100–105, 2003.

Klinker G. J., S. A. Shafer, and T. Kanade. A physical approach to color image understanding,. International Journal of Computer Vision, 4:7–38, 1990.

Swain M. J. and D. H. Ballard. Color indexing. International Journal of Computer Vision, 7:11–32, 1991.

Weiss Y., “Deriving intrinsic images from image sequences,” in Proc. Int. Conf. Comput. Vis., 2001, pp. 68–75.