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Shadow Detection and Removal Using Lab Colors, Morphological Operations and Chromaticity

Nimarta
Department of Computer Engineering
UCOE, Patiala
India

ABSTRACT

Shadows are physical phenomena observed in most natural scenes. Shadows in an image can cause segmentation, tracking, or recognition algorithms to fail. In this paper we have proposed shadow detection method based on Lab color space which efficiently detects the shadows in an image. we have used LAB color space, morphological operations and chromaticity as a combination to achieve final segmentation. The results obtained from the shadow detection techniques are very apt and satisfactory. As far as shadow removal technique using chromaticity is concerned, we have just worked upon the gray images and this technique can be applied to the colored images as well to remove the shadow and obtain the good results of an image. Moreover, some images give tremendously good results at some particular angle during the shadow removal process. So, the angle factor on which one can remove the shadow plays an important role to achieve the satisfactory results.

Keywords:- Shadow detection, shadow removal, morphological operations, LAB colors, chromaticity.

I. INTRODUCTION

A shadow shows up on a region when the light from a source can't achieve the region because of deterrent by an article. The shadows are now and again accommodating for giving helpful data about articles. Be that as it may, they cause issues in PC vision applications, for example, division, object location and item checking. In this manner shadow location and evacuation is a pre-handling undertaking in numerous PC vision applications [1].In different words, shadows made wherever an article clouds the light source, are an ever-exhibit part of our visual experience. Shadows can either help or perplex scene understanding, contingent upon whether we demonstrate the shadows or overlook them. On the off chance that we can recognize shadows, we can better confine objects, derive object shape, and figure out where objects contact the ground. Identified shadows likewise give signs to brightening conditions [3] and scene geometry [4]. Yet, in the event that we overlook shadows, spurious edges on the bound areas of shadows and disarray amongst albedo and shading can prompt errors in visual preparing. Therefore, shadow location has for some time been viewed as a urgent segment of scene elucidation (e.g., [5], [6]). However regardless of its significance and long convention, shadow recognition remains to a great degree testing issue, especially from a solitary picture. The primary trouble is because of the mind boggling connections of geometry, albedo, and brightening. Locally, we can't tell if a surface is dim because of shading or albedo, as delineated in Fig. 3, 4, 5. To figure out whether a region is in shadow, we should contrast the area with others that have the same material and introduction. Hence, most research spotlights on displaying the distinctions in shading, force, and composition of neighboring pixels or regions.

Figure1: Different kinds of shadows in image: (a) an overview of different kinds of shadows in one image, (b) cast shadow in a natural scene image [2].

II. CAST SHADOWS

Numerous PC vision applications managing video require distinguishing and following moving items. At the point when the objects of interest have a very much characterized shape, format coordinating or more modern classifiers can be utilized to straightforwardly section the articles from the picture. These procedures function admirably for very much characterized objects, for example, vehicles however are hard to actualize for non-inflexible questions, for example, human bodies. A more basic methodology for recognizing individuals in a video succession is to distinguish frontal area pixels, for instance by means of Gaussian mixture models [7, 8]. In any case, current procedures commonly have one noteworthy detriment: shadows have a tendency to be delegated part of the frontal area. This happens in light of the fact that shadows have the same development designs and have a comparative greatness of power change as that of the closer view objects [9]. Since give shadows can be a role as large as the genuine articles, their erroneous grouping as frontal area results in off base discovery and reductions following execution. Case situations where location and following execution are influenced include: (i) a few people are blended together on account of their cast shadows; (ii) the consideration of shadow pixels diminishes the unwavering quality of the appearance model for every individual, improving the probability of following misfortune. Both situations are represented in Figure 1. In that capacity, evacuating shadows has turned into an unavoidable stride in the execution of hearty following frameworks [10]. The last survey of shadow recognition and evacuation methods was done in 2003 by Prati et al. [11]. The survey classified shadow recognition strategies in a calculation based scientific classification. From every class, the creators chose one calculation to do a near assessment. The fundamental conclusion was that lone the least complex techniques were appropriate for speculation, yet in verging on each specific situation the outcomes could be essentially enhanced by including suppositions. As a result, there was no single strong shadow identification strategy and it was better for every specific application to build up its own system as indicated by the way of the scene.

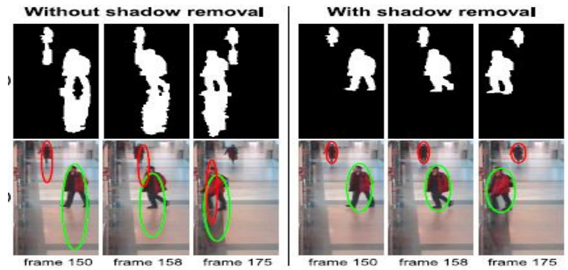


Figure 2 (a, b): tracking trajectory in a video with and without shadow removal.

Figure 2 is a case where the correct tracking trajectory can only be obtained when shadows are removed. **(a)** Foreground masks without shadow removal (left group) and with shadow removal (right group). **(b)** Tracking results, with the boundary of each object represented by an ellipse with a unique color. Without shadow removal the boundaries are unreliable, resulting in the loss of tracking of one of the objects.

III. LITERATURE REVIEW

A brief writing audit is required keeping in mind the end goal to comprehend work done by different researchers in this field. As presence of shadows may bring about major issues while dividing and following items: shadows can bring about article blending. Consequently, shadow identification is connected to find the shadow districts and recognize shadows from closer view objects. Now and again, shadow discovery is additionally misused to construe geometric properties of the items creating the shadow ("shape from shadow" approaches). Regardless of the distinctive purposes, perpetually the calculations are the same and can stretch out to any of these applications.

A. Prati et al [12] directed a study on distinguishing moving shadows; calculations managing shadows are arranged in a two- layer scientific classification by the creators and four agent calculations are portrayed in subtle element. The main layer characterization considers whether the choice procedure presents and adventures vulnerability. Deterministic methodologies utilize an on/off choice procedure, though factual methodologies use probabilistic capacities to portray the class enrollment. As the parameter determination is a significant issue for measurable techniques, the creators further separated factual strategies into parametric and nonparametric strategies. For deterministic methodologies, calculations are arranged by regardless of whether the choice can be upheld by model-based information. The creators surveyed four delegate strategies for there classifications of his scientific categorization and contended that Deterministic Model-based techniques [13] depend such a great amount on models of the scene that they unavoidably turn out to be excessively unpredictable and tedious.

T. Horprasert et al's technique [14] is a case of the factual nonparametric methodology and the creators signify it with image SNP. This methodology abuses shading data and utilizations a prepared characterize to recognize protest and shadows. I. Mikic et al [15] proposed a measurable parametric methodology (SP) and used both spatial and nearby components, which enhanced the recognition execution by forcing spatial imperatives.

R. Cucchiara et al's technique (DNM1) [16] and J. Stauder et al's work (DNM2) [17] were agents of deterministic non-model based technique. DNM1 depends on a supposition that shadows in picture don't change the tone of surfaces. The motivation behind why the creator assessed DNM2 is that it is the main work that handles the penumbra districts in picture. The overview of A. Prati et al essentially concentrates on the moving shadow location and the greater part of the papers they looked into don't inspect the self-shadow and normally they focus the consideration on umbra, considering the penumbra as a specific instance of umbra. It is on account of the separation between the articles and the foundation is immaterial contrasted with the separation of light sources to the items in a thruway scene and most or the greater part of the shadows are umbra or solid shadow.

S. Nadimi and B. Bhanu [18][19] proposed physical model based technique to distinguish moving shadows in video. They utilized a multistage methodology where every phase of the calculation expels moving item pixels with learning of physical models. Information Shadow Detection and Removal in Real Images: A Survey video edge is gone through the framework comprises of a moving item identification stage took after by a progression of characterizes, which recognize object pixels from shadow pixels and expel them in the hopeful shadow cover. Toward the end of the last stage, moving shadow cover and in addition moving item veil is gotten. Exploratory results exhibited that their methodology is hearty to generally diverse foundation surface, forefront materials and enlightenment conditions.

IV. PRESENT WORK

For machine discernment, a picture that incorporates shading is not generally required, and may perplex certain calculations to expel shading impact. Concerning people shading is not an issue and they can reason the scene which is shadowed and which is without shadow. To build the detectable quality of machines we have exhibited this work in which we attempted to expel shading zones in a picture. We utilized tone parameter to do our outcomes. In this work, we proposed two calculations for shadow discovery and shadow removal. Before understanding calculation, underneath is a portrayal of a few speculations utilized as a part of our work alongside their scientific conditions.

The following are ventures in shadow discovery calculation.

1) *Conversion of RGB color space to Lab color space*

To recognize shadow at first the RGB picture is changed over to a LAB proportional picture. The LAB shading space has three channels where L is the Lightness channel, A and B are the two shading channels. The L channel has values extending from 0 up to 100, which relates to various shades from dark to white. The A channel has values extending from −128 up to +127 and gives the red to green proportion. The B channel likewise has values going from −128 up to +127 and gives the yellow to blue proportion. Subsequently, a high esteem in An or B channel speaks to a shading having more red or yellow and a low esteem speaks to a shading having more green or blue. Since the shadow areas are darker and less enlightened than the surroundings, it is anything but difficult to find them in the L channel subsequent to the L channel gives delicacy data.

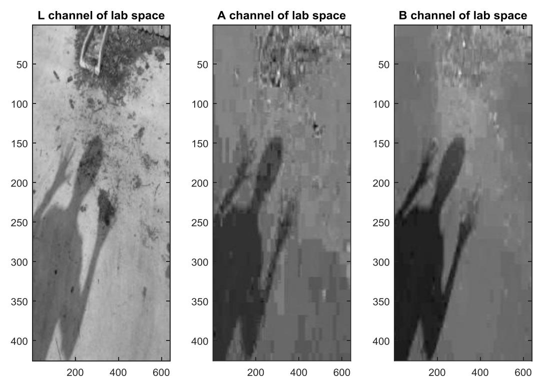


Figure 3: (a) L channel (b) a channel (b) b channel of Lab color space

2) Usage of mean and standard deviation

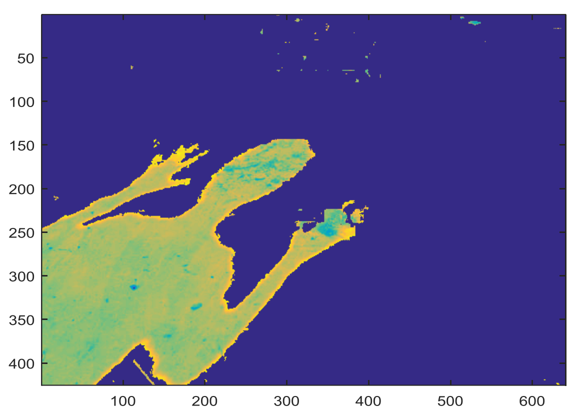


Figure 4: Results after threshold using mean and standard deviation

3) Morphological operations

Cleaning, a morphological operation can evacuate disengaged pixels. The misclassified pixels are expelled utilizing widening took after by disintegration. Additionally zone based thresholding is done, so that lone areas with various pixels more noteworthy than an edge can be considered as shadow locales. All these morphological operations hence wipe out misclassification of pixels.

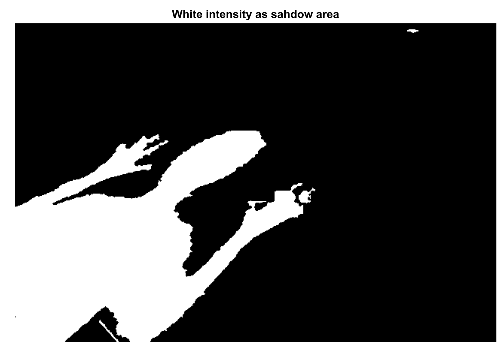


Figure 5: Results after filtering process using morphological operations

4) Applying associated part naming to get the greatest article in the picture conveying cast shadow

In this we utilized bwlabel charge for getting the articles as per availability and use territory property of 'region props summon to get the greatest range component.

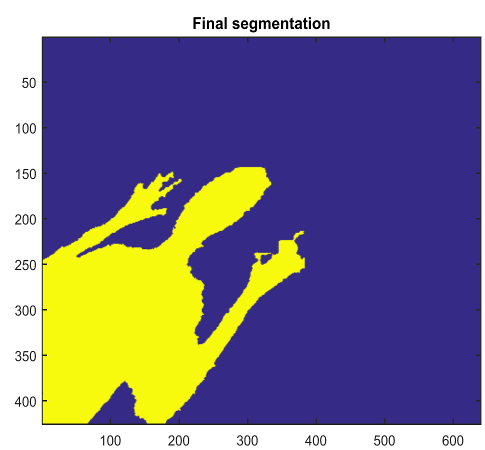


Figure 6: Results after connected component labeling

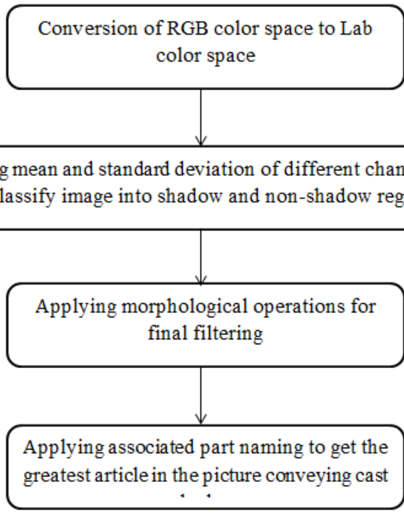
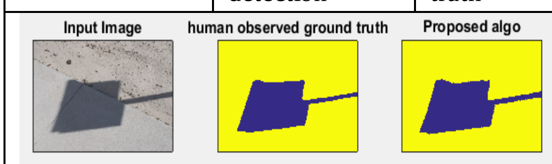
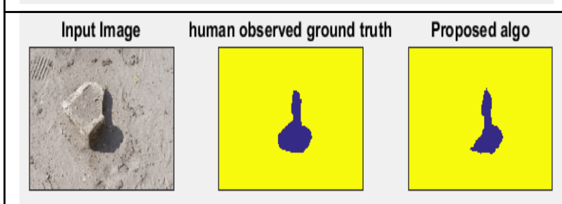
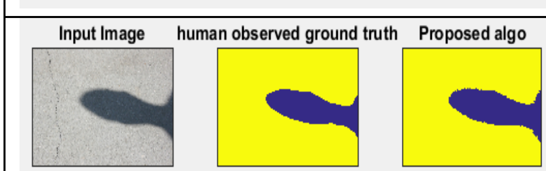


Figure 7: Flowchart of the proposed algorithm

Original image	Shadow detection	Ground truth	TP	FN	TN	FP	Specificity	Sensitivity
			131706	186	33252	2356	0.99	0.93
			158393	1947	6615	545	0.99	0.92
			137966	26	28304	1204	0.99	0.96
			140461	0	23146	3893	1	0.87

Results

Below are the results for sensitivity and specificity values in order to get accuracy of the algorithm in detecting shadow region.

	139358	3285	22426	2431	0.98	0.91

V. CONCLUSION

The title of the dissertation that is “Shadow detection and removal using LAB color space, morphological operations and chromaticity” is well explanatory in its own terms. Many different techniques have been used in the shadow detection as well as in the shadow removal but here we have used only LAB color space, morphological operations and chromaticity. The results obtained from the shadow detection techniques are very apt and satisfactory. As far as shadow removal technique using chromaticity is concerned, we have just worked upon the gray images and this technique can be applied to the colored images as well to remove the shadow and obtain the good results of an image. Moreover, some images give tremendously good results at some particular angle during the shadow removal process. So, the angle factor on which one can remove the shadow plays an important role to achieve the satisfactory results.

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