SHADOW IDENTIFICATION AND CLASSIFICATION USING INVARIANT COLOR MODELS

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ABSTRACT

A novel approach to shadow detection is presented in this paper. The method is based on the use of invariant color models to identify and to classify shadows in digital images. The procedure is divided into two levels: first, shadow candidate regions are extracted; then, by using the invariant color features, shadow candidate pixels are classified as self shadow points or as cast shadow points. The use of invariant color features allows a low complexity of the classification stage. Experimental results show that the method succeeds in detecting and classifying shadows within the environmental constrains assumed as hypotheses, which are less restrictive than state-of-the-art methods with respect to illumination conditions and scene's layout.

1. INTRODUCTION

Applications such as image databases and satellite imaging may require the identification of objects through segmentation. The information about the shape and the color of the segmented objects is then exploited. This information can be distorted by different kinds of noise which are introduced by the acquisition process or by natural causes like shadows. Shadows occur when objects totally or partially occlude direct light from a source of illumination. Shadows can be divided into two classes: cast and self shadows. A cast shadow is projected by the object in the direction of the light source, a self shadow is the part of the object which is not illuminated by direct light. The presence of cast shadows in an image can modify the perceived object shape, while the presence of self shadows modify the perceived object shape and its color. In order to provide a correct description of the objects, shadows should be identified and classified.

Relatively limited work can be found in the literature in the field of shadow detection. Two different approaches have been followed, the first based on models, the second based on shadow properties.

In the first approach, models are used to represent the *a priori* knowledge of the three-dimensional geometry of the scene, the objects, and the illumination [1, 5, 7]. Constrained environments such as traffic scenes [5] or buildings [1, 7] are considered, and the direction of the light is assumed to be known. These geometry-based approaches have two major drawbacks. Simple rectilinear models (e.g. buildings and vehicles) can be used only for simple objects, but not for more complex scenes (containing persons, for instance). In addition, the *a priori* knowledge of the illumination and the 3-D geometry of the scene is not always available. These approaches have thus a limited application range.

The second approach is more general and identifies shadows by exploiting their properties in geometry, brightness and color [2, 8]. In [8], a shadow identification and classification algorithm for gray-scale images is presented. The method is based on the analysis of shadow intensity and geometry in an environment with simple objects and a single area light source[1]. Only simple scenes, without occlusions between objects and shadows, are considered. The classification into cast and self shadows is based on the assumption that the intensity values of pixels in a self shadow region are larger than those in the corresponding cast shadow region. This represents a limitation of the method since it leads to a misclassification if objects are significantly darker than the background or if a cast shadow receives light reflected from another object. This makes the cast shadow brighter than the self shadow.

A system that combines color information and geometry information to recognize shadows is described in [2]. It detects cast shadows, but does not consider self shadows. The method is applicable to more complex scenes compared to those analyzed in [8]. On the other hand, it presents a very strong limitation that makes it unusable in many applications. An active observer is introduced who is allowed to cast its own shadow. From this shadow the direction of the light source is empirically calculated. By using this information, shadows are confirmed among the extracted candidate shadow regions.

In this paper, we present an approach for the identification and classification of shadows which overcomes some of the above-mentioned limitations, namely the range of applicability with respect to the illumination conditions, and with respect to the need of an active observer. The proposed approach is based on shadow properties and exploits color information. The method is also applicable when no *a priori* knowledge of the scene is available and when objects of different type are present.

The paper is organized as follows. In Sec. 2, the proposed shadow detection method is described. Experimental results are presented in Sec. 3, and in Sec. 4 we draw some conclusions.

2. PROPOSED APPROACH

The goal of the proposed algorithm is the extraction and the classification of shadows in color images. The method works under the following hypotheses on the scene and on the lighting conditions.

[1] An area light source is a source of illumination presenting a certain extent (in contrast to a point light source).

A simple environment is assumed where shadows are cast on a flat, or nearly flat, nontextured surface (as in [8]). Objects are uniformly colored. Only one light source illuminates the scene, and shadows and objects are within the image. The light source must be strong, thus shadows are well visible. No other restriction to the lighting is assumed, and occlusion between objects and shadows is considered. This allows to consider more complex scenes with respect to the method in [8].

Color information is exploited by considering color features that show invariance properties with respect to changes in the illumination conditions, that is to shadows and shading. They are introduced in Sec. 2.1.

Image areas which are darker than their surroundings are identified as shadow regions. They are then classified as cast shadows if they belong to the background of the scene or as self shadows if they are part of an object. Sections 2.2 and 2.3 describe the two levels of the detection process.

2.1. Invariant color models

We propose to exploit color information for shadow detection by using the invariance properties of some color transformations. These transformations (photometric color invariants) are functions which describe the color configuration of each image point discounting shadings, shadows and highlights. They are invariant to a change in the imaging conditions, such as viewing direction, object's surface orientation and illumination conditions.

Among the traditional color features, normalized *rgb*, hue (*H*) and saturation (*S*) are invariant features to shadows and shading. In addition to these well-known color spaces, new invariant color models, $c_1c_2c_3$ and $l_1l_2l_3$ are proposed in [3].

We have evaluated the behavior of all the invariant features cited above, namely *rgb*, *H*, *S*, $c_1c_2c_3$ and $l_1l_2l_3$, for shadow detection. The best results are obtained using the $c_1c_2c_3$ model, that has been adopted in our method. The $c_1c_2c_3$ color invariant features are defined as follows:

$$c_1 = \arctan\left(\frac{R}{max(G,B)}\right) \tag{1}$$

$$c_2 = \arctan\left(\frac{G}{max(R,B)}\right) \tag{2}$$

$$c_3 = \arctan\left(\frac{B}{max(R,G)}\right) \tag{3}$$

for R,G, and B representing the red, green, and blue color components of each pixel in the image.

2.2. Shadow candidates identification

The first step toward identifying shadows involves the exploitation of the luminance properties of shadows. Shadows result from the obstruction of light from a light source. Thus, the luminance values in a shadow region are smaller than those in the surrounding lit regions.

In [8], a scheme that extracts, as potential shadows, regions that are darker than their surroundings is proposed. We have modified this method in order to apply it to a portion of the image. This portion is individuated by an edge map. The edge map is obtained by applying a Sobel operator on the luminance component of the input image.

Horizontal and vertical scanning is performed on the edge map, in order to find the outer points of the edge map. The intensities at the detected points are used as reference to determine if the pixels in the inner part of the edge map are darker and therefore candidate to be shadow points.

Since luminance is a color feature that is sensitive to shadows and shadings, the map contains both object and shadow edges (Fig. 1(b)). By using this edge map in the dark regions extraction process, we restrict the search for shadow candidate regions in the portion of the image that is occupied by the object and its cast shadow.

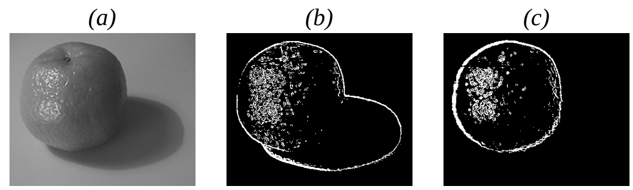

Fig. 1. Edge detection on luminance and photometric invariant: (a) original image; (b) edge map of the luminance component containing object and shadow boundaries; (c) color edge map on invariant color features containing only the object boundaries.

This allows to overcome two limitations of the method described in [8]: the hypothesis on the intensity on image borders and the setting of a parameter for the dark regions identification. First, the scheme presented here holds even when the intensities on image borders are lower than those in shadows, that is for example in the case of a focused light source. Then, the use of the edge map avoids the need of the parameter for determination of dark pixels.

Since the edge map may not form closed contours, some shadow points may be misclassified. To overcome this problem and to improve the performance of the detection algorithm, morphological processing is applied to the luminance edge map. This processing allows to close the contours in the detected edge map and to obtain a better performance of the dark regions extraction module.

2.3. Shadow classification

Once the dark regions have been extracted from the image, color information can be used to classify shadow regions on the object (self shadows) and shadow regions on the background (cast shadows). Photometric color invariants are exploited in this step of the recognition process.

By performing edge detection on the invariant color features, an edge map[2] which does not contain the edges corresponding to shadow boundaries is obtained (Fig. 1(c)).

The color edge map and the dark regions map are then used as input for the classification level.

The process for the classification of dark regions is similar to that used for their detection. The input color edge map is scanned in the horizontal and vertical directions to find the outer points of the edge map. The detected points indicate the outer edge points

[2]The color edge map is the result of a logical OR-connection operation on the edge maps obtained with the Sobel operator on each color component.

on the object. Points in the dark region mask that lie within the detected edge points are classified as self shadow points. The other points are classified as cast shadow points.

Due to noise in the invariant color features, isolated edge points may be detected far outside the object contours. This could lead to misclassification of some cast shadow as self shadows. A morphological processing of the final cast and self shadow mask is applied to reduce such misclassification and to improve the method's performance.

Another constraint is due to the instability of the invariant color features for low values of saturation and intensity. For this reason, for a correct color edge detection, saturation and intensity values have to be larger than 5% of their total range [4, 6].

By exploiting color information, we overcome the limitations of the dark regions classification process of [8], which assumes that cast shadow pixels are darker than self shadow pixels as an empirical criterion for shadow classification. This may not always be true. The criterion exploited here is the definition of cast and self shadow, stating that self shadows belong to objects, while cast shadows lie on the background. This represents a more realistic criterion, that makes the method more general.

Moreover, the use of color invariants in the classification level reduces the complexity of the proposed method with respect to [8]. No further feature analysis on dark regions, nor hypothesis integration are required.

The block diagram of the proposed shadow identification method is depicted in Fig. 2. The complete process can be summarized as follows:

1. The luminance image, which is sensitive to shadows, and the color components of the invariant color model, are obtained through a color space conversion step.
2. Edge detection on the luminance image is performed.
3. The obtained edge map is used, together with the luminance image, as the input for a scheme that extracts regions in the scene that are darker than their surroundings. Dark regions are candidate shadow regions.
4. Edges on the photometric invariant color space are obtained to find object contours and discount shadow contours.
5. Dark regions that are not contained in the object contours are classified as cast shadow regions, while dark regions that are inside the detected object contours are classified as self shadow regions.

This process is valid when there is only one object in the image. In the case of a scene composed by multiple objects, it is possible to limit the analysis to each single object by applying a connected component labeling.

3. EXPERIMENTAL RESULTS

The results of the proposed shadow identification and classification algorithm are presented in this section. The test set is composed of color images taken under the hypotheses commented in Sec. 2. A selection of these images is presented in the following (Fig. 3(a)). A single object casting its shadow is depicted in the first (*Orange*) and in the second row (*Apple*). A more complex scene is shown in the third row (*Kolla*). There are two objects and occlusion between objects and shadows is present. The object on the left violates the assumption on the color of objects in the scene. This allows us to test the robustness of the method when varying the working hypotheses.

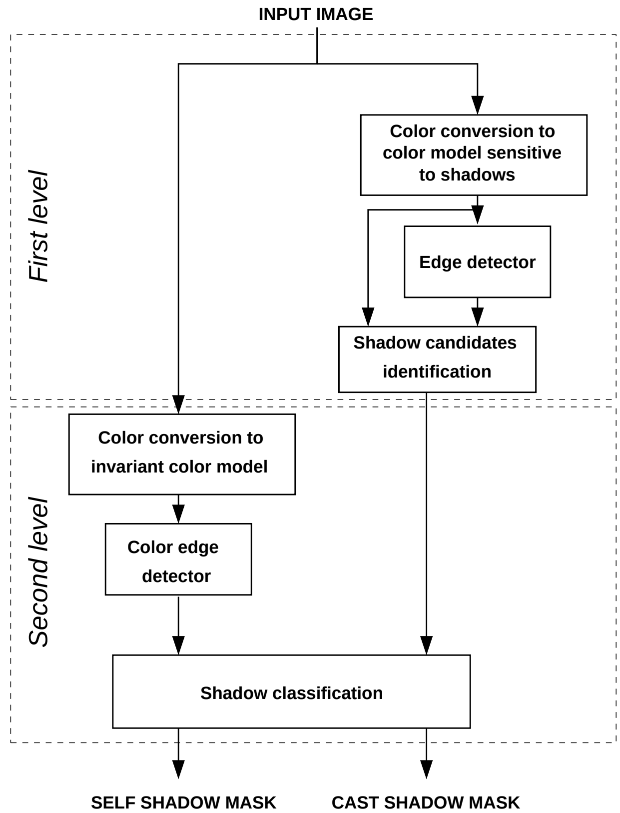

Fig. 2. Block diagram of the proposed shadow identification and classification method.

The edge detection step discussed in the previous section requires the setting of a threshold in order to obtain a binary mask in the edge detection process. The values selected for the different test images are reported in Table 1. The values for the color edge detector are higher than those for the luminance edge detector. In the first case, a lower sensitivity of the edge detector is required to reduce the number of edge points detected, due to noise, far outside the object contours. In the second case, a higher sensitivity allows to obtain a map where edges form as much as possible closed contours.

For *Orange* and *Apple*, the masks (b) and (c) show that the cast shadow and the self shadow have been correctly detected by the algorithm.

In the case of *Kolla*, the algorithm has been applied to the two

	luminance	color
Orange	0.060	0.116
Apple	0.052	0.169
Kolla	0.065	0.100

Table 1. Value of the thresholds for the luminance and the color edge detector on the different test images.

portions of the image that contain the two objects. The resulting shadow masks have been then integrated into the final cast and self shadow masks. This example allows us to analyze the behavior of the proposed method in an extreme case with respect to the working hypotheses.

Results show that the object on the right has been misclassified as a shadow and that the classification step of the algorithm has erroneously assigned some candidate shadow points on both objects to the final cast and self shadow masks. The right object is very dark and this implies two types of problems when applying the shadow recognition algorithm.

First, the dark regions extraction step classifies the object as a potential shadow, since it is one of the darkest regions in the image. Since it was part of the dark regions mask, the dark object results in the final self shadow mask.

Second, the performance of the color edge detector on the $c_1c_2c_3$ components is unsatisfactory on the dark object and on the darkest part of the object on the left because of the instability of the color features for low values of saturation and intensity, as discussed in Sec. 2.3. For this reason, some shadow points have been misclassified, especially near object borders.

However, it is interesting to note that the method has detected the shadow that the object casts in the direction of the viewer. The boundary between this shadow and the object is difficult to see when looking at the original image. The use of photometric invariants has allowed, in this case, to correctly distinguish between shadow and object.

(a) *(b)* *(c)*

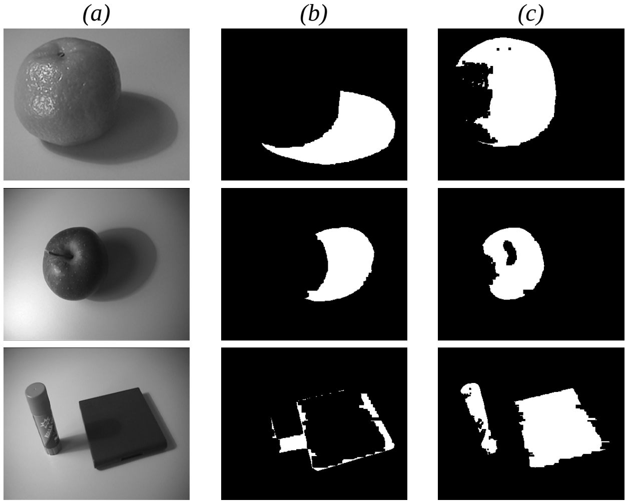

Fig. 3. Shadow detection and classification results of the proposed method. (a) original image, (b) cast shadow map, (c) self shadow map.

4. CONCLUSIONS

A novel method to identify and to classify shadows in color images has been presented. Both luminance and color information are used in shadow identification. By exploiting luminance information, regions darker than their surroundings are extracted as shadow candidates. The regions include self shadows on the object and cast shadows on the background.

Color edge detection on color invariant models is used to obtain object edges discounting shadow edges. Shadow candidate points are classified as self shadow points if they lie within the detected object edges, otherwise they are labeled as cast shadow points. The proposed method succeeds in detecting and classifying shadows within environmental constrains that are less restrictive than other methods in literature.

Future work will focus on defining a strategy to describe the color of an object discounting the effect of the self shadow. In addition, a technique that enables to improve the quality of the extracted contours will be investigated. This will allow to improve the accuracy of the classification, by reducing the number of misclassified pixels. Finally, this work will be extended in order to be applied to video sequences. In this case, the additional information given by time will be exploited.

5. REFERENCES

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