

A Study and Analysis of Colour Space selection for Insignificant Shadow Detection

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Abstract

Though shadows provide realism to the scene, it is found to be problematic in many computer vision and cognitive science applications. Many researches are going on to detect and remove them significantly. There are variety of features that can be used for identifying shadows. This papers experiments the importance of Colour space selection to detect shadow from scenes and videos. Colour features can improve the performance of object tracking and scene understanding. Hence, several well known Colour spaces are experimented. From the outcome, the performance of shadow detection can be improved significantly through the appropriate Colour space selection strategy. The experimental results on real-time scenes show that proposed Colour space is efficient over other Colour spaces.

Keywords: Shadow Detection, Colour Space, Shadow Identification, Natural Scene, shadow removal

1. Introduction

The recent real-time problems of computer vision interested in, tracking the objects and their movements. Visual object tracking uses cameras to track target objects in the environment, which has many applications nowadays, such as intelligent surveillance, medical care, intelligent transportation and human-machine interaction [1]. However, it is still a challenging task because of background noises, occlusions, illumination changes and fast motion. Colour histograms have become popular and important descriptors for object tracking, due to their simplicity, effectiveness and efficiency. However, they suffer from illumination changes. Colour is one among the prominent visual features used for object detection and tracking systems, especially in the arena of robotic vision and machine perception.

Shadows are ubiquitous in natural scenes, and their removal is an interesting and important area of current research. Apart from a few geometry based

approaches which are suited to specific conditions [2] shadow detection is usually done by Colour based photometric methods.

Still image based methods [3] attempt to find and remove shadows in the single frames independently. However, these models have been evaluated only on high quality images where the background has a uniform Colour or texture pattern, while in video surveillance; images with poor quality and resolution must expected. The authors in [4] note that their algorithm is robust when the shadow edges are clear, but artifacts may appear in cases of images with complex shadows or diffuse shadows with poorly defined edges. For practical use, the computational complexity of these algorithms should be decreased [3]. Some other methods focus on the discrimination of the shadow edges, and edges due to objects boundaries [5] [6]. However, it may be difficult to extract connected foreground regions from the resulting edge map, which is often ragged [5]. Complex scenarios containing several small objects or shadow-parts may be also disadvantageous for these methods. Prati et al., [7] gives a thematic overview on shadow detection for video surveillance. The methods are classified into groups based on their model structures, and the performances of the different model-groups are compared via test sequences.

Colour model is a method for explaining the properties or behavior of a Colour within some particular context. The authors note that the methods work in different Colour spaces [8]. However, it remains open-ended, how important are the appropriate Colour space selection, and which Colour space is the most effective regarding shadow detection. For the above reasons, the main issue of this paper is to present an experimental comparison of different Colour models regarding shadow detection on the casually captured scenes and videos. For the comparison, a general framework to work with different Colour spaces is proposed. During the development of this framework, the main approaches in the state-of-the art have been carefully considered. It is noted that an experimental evaluation of Colour spaces have been already done for edge classification in [9], and some other literatures too. But in the current research, the main focus is the detection of the shadowed and foreground regions, which is a practically an intricate problem.

2. The Colour based Techniques

The Colour technique is based on the fact that the Colour tune values of a shadow region are the same as the values in the background while the intensity values are different [10]. This technique attempts to find the Colour features that are illumination invariant using the Colour differences in the shadowed region and image and employs the spectral information of the foreground region, background region and shadow region to detect shadows [11]. The Colour techniques are useful for the Colour information in the HSV Colour space and RGB Colour space [12]. The weakness of this approach appears more when the objects have a similar intensity or brightness as the shadows or when the Colour of the objects is the same as the Colour of the background region or even when the objects are darker than the background.

In these cases, the foreground pixels will be misclassified as shadow pixels or holes will be created within the object [13]. Overall, by converting Colour spaces, this is difficult to detect all shadow pixels stably [14]. In addition, since Colour is the primary cue to identify a shadow pixel in Colour images, this technique might not Maryam Golchin et al., [16] work with black and white images [Zhu J] the ratio of Colour channels over Near Infrared (NIR) image is used. Their method is automatic and reliable for mosaiced images. Also, Sun and Li et al., [17] proposed a combined Colour model using the ratio of hue over intensity in HSI Colour model and photometric Colour invariant c1c2c3 Colour model.

Overall there are five different kinds of information to detect shadows namely, texture information, temporal information, grey scale information, Colour information and edge information. Texture information such as Local Binary Pattern (LBP) is only helpful to detect foreground objects which are a combination of the objects and shadow areas. It means this method is not able to distinguish the objects from the shadows. Due to this disability, this kind of information does not preserve affective information for the shadow detection process. Note that this study is going to detect shadow pixels from objects. As the second utilized information in the shadow detection process, the temporal information is also able to detect motions in an image. Where each motion is a combination of both an object and a shadow area and again this method does not provide valuable information either. Another kind of information to detect the shadow pixels is the Colour information [15].

The Colour tune values, as colour information, present valuable information to detect shadows that cannot be obtained using the grey scale information. As a result, the Colour information is selected and the grey scale information is omitted

in this study [15]. Last but not least, use of edge information is based on the fact that shadow boundaries are strict and connected to the object while the edges are faint next to the background [17]. Therefore, this information is help full to detect shadows. As a conclusion, from the explained five types of information, Colour information and edge information are selected in this research.

3. Feature vector for Shadow detection

Here, the features for shadow detection are constructed by including some challenging environmental conditions [9]. The approach on shadow detection uses shadow variant and invariant features, from the feature importance measure analysis. The shadow variant features considered are Intensity/ chromaticity difference, Illumination changes, Local max, smoothness and skewness. The shadow invariant features supporting are Gradient similarity and Texture similarity. Finally, the efficiency of the proposed scheme is validated by variety of experiments with shadow-illness criteria using the colour spaces discussed in the next section.

4. Colour Spaces

Given the illumination changes, the Colour invariance properties of Colour histograms can be analyzed. A Colour histogram depicts the Colour distribution of the objects in a specific Colour space, e.g., RGB, HSV and HSI. Therefore, the Colour constancy of Colour spaces determines the Colour invariance properties of Colour histograms [23]. This section describes different types of Colour spaces.

4.1 RGB space

The RGB Colour space has three channels: red, green, and blue. A 3D histogram can be derived by calculating the number of pixels that have Colours in a fixed range which depends on the number of bins. The RGB histogram has no illumination invariance properties [24].

4.2 nRGB Space

The nRGB Colour space is the normalized RGB Colour space [5]

$$[nR, nG, nB] = [R \frac{R}{R+G+B}, \frac{G}{R+G+B}, \frac{B}{R+G+B}] \quad (5)$$

$$nB = 1 - nR - nR \quad (6)$$

The nRGB histogram is invariant to light intensity change. Since channels are only used in the experiment.

4.3 HSV Colour Space

The Hue Saturation Value (HSV) and Hue Saturation Intensity (HSI) Colour spaces are

similar. These Colour spaces are similar to human description of a Colour [5]. Since they can be obtained by a linear transformation from the RGB Colour space, they inherit drawbacks from RGB Colour space. In HSV Colour space, the convention from RGB Colour space is obtained as follows:

$$H = \cos^{-1} \left(\frac{0.5X(R - G) + (R - B)}{\sqrt{((R - G)^2 + (R - B)X(G - B))}} \right)$$

$$S = \frac{\text{Max}(R+G+B) - \text{min}(R+G+B)}{\text{max}(R+G+B)}, V = \text{max}(R+G+B) \quad (7)$$

4.4 C1C2C3 Colour Space

The C1C2C3 Colour Space is introduced in [25]. This Colour space is referred as being invariant to shadows and shading. The conversion from RGB Colour space is as follows:

$$C_1 = \arctan \left(\frac{R}{\text{max}(G,B)} \right), C_2 = \arctan \left(\frac{G}{\text{max}(R,B)} \right),$$

$$C_3 = \arctan \left(\frac{B}{\text{max}(R,G)} \right) \quad (8)$$

4.5 h1h2h3 Colour Space

The rgb space has showed itself to be invariant to illumination intensity. The l1l2l3 space has shown invariance with respect to highlights and illumination intensity [26]. A new space introduced which is only invariant with respect to highlights. This space preliminarily called the h1h2h3 space and defined as follows:

$$h1 = R - G, h2 = G - B, h3 = B - R \quad (9)$$

4.6 CIE-LAB Colour Space

The CIELAB space has been designed to be a perceptually uniform space [27]. A system is perceptually uniform if a small perturbation to a component value is approximately equally perceptible across the range of that value. A perceptual difference between two points in the CIELAB space can be represented closely by the Euclidean distance (square norm) measure [17]. The XYZ to CIELAB transformation is shown in equation:

$$L = \begin{cases} 25 \left[100 \frac{Y}{Y_0} \right]^{1/3} - 16 & \text{if } \frac{Y}{Y_0} \geq 0.08856 \\ 903.3 \frac{Y}{Y_0} & \text{otherwise} \end{cases} \quad (10)$$

5. Performance Evaluation

The evaluations were done through various datasets in both quantitative and qualitative methods. The benchmark images are tested and results are shown in figures and tables. In this experiment, two sets of Ψ values corresponding to manually marked foreground and shadowed pixels are collected, respectively. It is investigated to know how many pixels are classified properly by the ellipse model with different Colour spaces. The number of correctly

identified foreground pixels of the evaluation sequence denoted by T_F . Similarly, T_S is introduced for the number of well classified shadowed points, M_F and M_S is the number of misclassified foreground, and shadowed ground truth points, respectively. First, the Recall (R) and Precision (P) rates of foreground detection are defined [28]:

$$\text{Recall: } R = \frac{T_F}{T_F + M_F}, \text{ Precision: } P = \frac{T_F}{T_F + M_S} \quad (11)$$

In the further tests, the F-measure is used [23] which combines recall and precision in a single efficiency measure (it is the harmonic mean of precision and recall):

$$F - \text{Measure} = \frac{2.R.P}{R+P} \quad (12)$$

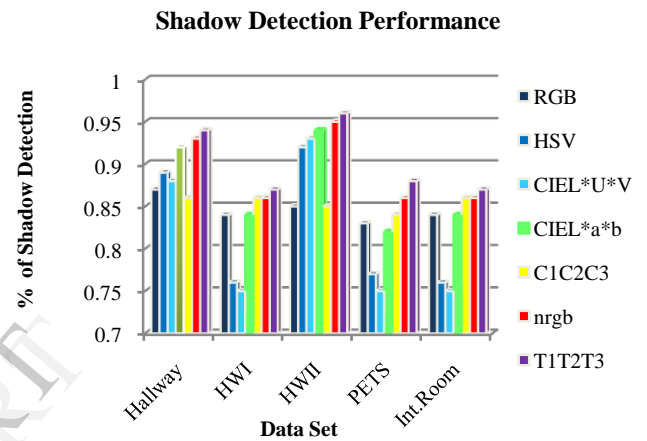


Fig1. Evaluation of Shadow Detection Performance

6. Conclusion

This paper examines the selection of suitable Color space for shadow detection. A framework is developed for this task, which can work under different Color spaces. Mean-while, it can detect shadow significantly from different scene classes

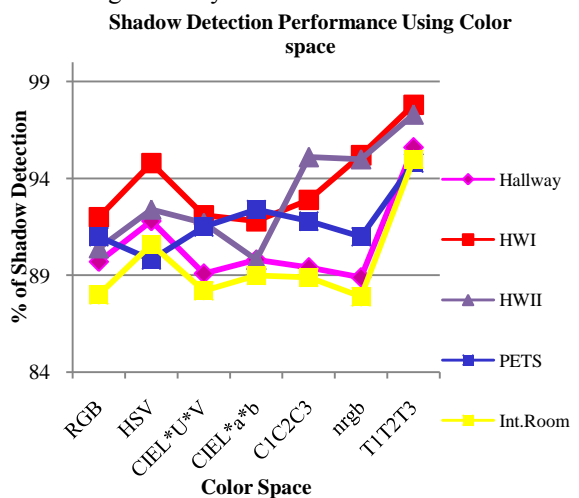


Fig2. Evaluation of F-Measure

Colour space	Hallway	HWI	HWII	PETS	Int. Room
RGB	92.33	90.47	90.71	90.01	90.01
HSV	94.74	92.86	90.11	91.43	91.43
CIE LUV	92.01	91.41	91.18	89.36	89.36
CIE Lab	91.89	90.15	92.78	89.99	89.99
$C_1C_2C_3$	93.11	95.39	92.09	89.74	89.74
nrgb	95.41	95.48	91.41	88.83	88.83
$T_1T_2T_3$	97.42	96.73	94.65	95.66	95.66

Table 1. Shadow Detection Accuracy

conditions and it has some common parameters to be properly validating the Colour spaces. In our case, the transition between the background and shadow domains is described by statistical distributions. With this framework, several well known Colour spaces are compared in terms of both quantitative and qualitative evaluations and observed that the Colour space selection issue is more important. Regarding the segmentation of different kinds of objects under varying environmental conditions is evident in results, with appropriate selection of Colour space. The proposed method is validated on well-known benchmark datasets of indoor and outdoor scenes and videos, which contain different kind of objects and different environmental conditions. Experimental results show that $T_1T_2T_3$ Colour space is the most efficient in comparison with other Colour spaces.

Methods	Colour space	Colour channels	Outdoor / Indoor tests
Cavallaro et al.,	Rg	Invariant	Both
Salvador et al.,	$C_1C_2C_3$	invariant	Both
Paragios et al.,	Rg	Invariant	Indoor
Mikic et al.,	RGB	1	Outdoor
Rittscher et al.,	Grayscale	2	Outdoor
Wanget al.,	grayscale	2	Indoor
Cucchiara et al.,	HSV	1,33	Both
Birsson et al.,	CIE L *u*v*	2	Indoor
Rautianinen et al.,	CIE L*a*b*/HSV	N. a	Outdoor
Siala et al.,	RGB	N. a	Outdoor
Proposed	All from above + $T_1T_2T_3$	2	Both

Table 2. Related Works of significant authors

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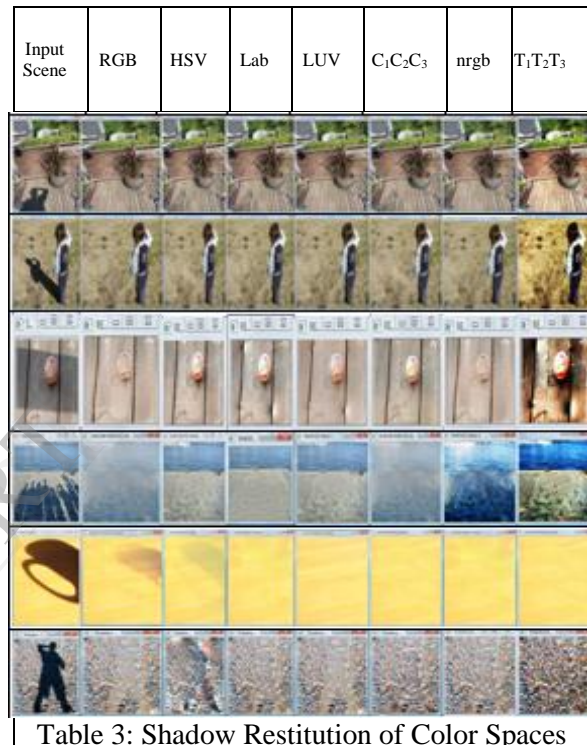


Table 3: Shadow Restitution of Color Spaces

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