An Analysis of Suitable Color Space

Muthukumar Subramanyam
HOD CSE / IT, IIIT Tamilnadu, A Government of India Institute under Ministry of HRD

An Analysis of Suitable Color Space for Visually Plausible Shadow-free Scene Reconstruction from Single Image

Krishnan Nallaperumal[1], Muthukumar Subramanyam [2], Ravi Subban [3],
Pasupathi Perumalsamy[1], Shashikala Durairaj[1], Gayathri Devi .S[1], Selva Kumar .S[1]

[1]Centre for Information Technology and Engineering, Manonmaniam Sundaranar University, Tirunelveli, India
[2] Department of CSE, National Institute of Technology Puducherry, Pondicherry, India
[3]Department of Computer Science, Pondicherry University, Puducherry, India
krishnan@ieee.org, sm.cite.msu@gmail.com, sravicite@gmail.com, pp.cit.msu@gmail.com, shashikalait85@gmail.com

Abstract - Color features can improve the performance of object tracking under various lighting conditions, such as light sources, shadows and highlights. The same object under different lighting conditions can have dissimilar appearances in images recorded by the same camera. Therefore, color invariant features which are robust to lighting condition changes are desired for object recognition and tracking. In this paper, the color space selection for shadow detection in casually captured scenes is addressed. The performance of shadow detection can be improved significantly through appropriate color space selection strategy. Hence, several well known color spaces are experimented. It demonstrate that the selection of color space is important for shadow detection and extraction processes. The experimental results on real-life scenes show that proposed color space is efficient over other color spaces.

Keywords - ***Shadow Detection, Color Space, Shadow Identification, Natural Scene, Shadow Reconstruction***

I. 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. Color histograms have become popular and important descriptors for object tracking, due to their simplicity, effectiveness and efficiency [2]. However, they suffer from illumination changes.

Color is the one among the prominent visual features used for object detection and tracking systems, especially in the robotic vision and machine perception. Visual object tracking is a process of continuously estimating the state of an object in an image given prior states from previous frames. The state of an object can be position, velocity, shape, size and so on. Object tracking can be difficult due to noise, partial or full occlusions, complex object motion, and shape and illumination changes. In order to deal with these difficulties, object tracking algorithms require robust measurements which can describe the appearance of objects correctly when the environmental conditions change [3].

Shadows are ubiquitous in natural scenes, and their removal is an interesting and important area of research [4]. Apart from a few geometry based approaches which are suited to specific conditions. Shadow detection is usually done by color filtering [5]. Still image based methods 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 color or texture pattern, while in video surveillance; images with poor quality and resolution must expected. The authors 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. Some other methods focus on the discrimination of the shadow edges, and edges due to objects boundaries. However, it may be difficult to extract connected foreground regions from the resulting edge map, which is often ragged. Complex scenarios containing several small objects or shadow-parts may be also disadvantageous for these methods. Prati et al., [6] 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.

Color model is a method for explaining the properties or behavior of a color within some particular context. The authors note that the methods work in different color spaces. However, it remains open-ended, how important are the appropriate color space selection, and which color space is the most effective regarding shadow detection [5]. For the above reasons, the main issue of this paper is to present an experimental comparison of different color models regarding shadow detection on the casually captured scenes and videos.

For the comparison, a general framework to work with different color 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 color spaces have been already done for edge classification in Khan et al., [7], and some other literatures too. But in the current research, the main focus is the detection of the shadowed

978-1-4799-1597-2/13/$31.00 ©2013 IEEE

and foreground regions, which is a practically an intricate problem.

II. FEATURE VECTORS FOR SHADOW DETECTION

Here, the features for shadow detection are constructed by including some challenging environmental conditions [8]. The physical approach on shadow detection is introduced in the section and also the assumptions that may fail in real-world scenes are discussed [9]. Instead of constructing a more complex model, the appearing artifacts with statistical descriptions are sufficient to overcome the problems. Finally, the efficiency of the proposed model is validated by experiments.

Human visual system [10] seems to utilize the following observations for reliable shadow detection:

- Shadow is dark but does not change significantly neither the color nor the texture of the background covered [11].
- Shadow is always associated with the object that cast it and to the behavior of that object (e.g. if a person opens his arms, the shadow will reflect the motion and the shape of the person).
- Shadow shape is the projection of the object shape on the background. For an extended light source (not a point light source), the projection is unlikely to be perspective.
- Both the position and strength of the light sources are known.
- Shadow boundaries tend to change direction according to the geometry of the surfaces on which they are cast.

The important *shadow variant features* chosen are as follows [12]:

- *Intensity Difference:* Since shadows are expected to be relatively dark, the statistics about the intensity of image segments in neighboring pixels measure the intensity difference using their absolute differences. In neighboring segments the difference of intensity values are measured. Also the feature vector with the averaged intensity value and the standard deviation are taken into account.
- *Illumination changes:* This change in a single image can be modeled by a linear transformation [14] of diagonal-offset model. The five basic types of the illumination changes can be defined [15], as follows: (a) Light intensity changes, (b) Light intensity shifts, (c) Light intensity changes and shifts, (d) Light color changes and (e) Light color change and shifts.
- *Local Max:* In a local patch, shadows have values that are very low in intensity; therefore, the local max value is expected to be small. On the contrary, non-shadows often have values with high intensities and the local max value is expected to be large.
- *Smoothness:* Shadows are often a smoothed version of their neighbors. This is because the shadows tend to suppress local variations on the underlying surfaces [13]. The method subtracts a smoothed version of the image from the original version. Already smooth areas will have small differences where as highly varied areas will have large differences. To measure the smoothness, the standard deviations are used from neighboring segments.
- *Skewness:* Several statistical variables (standard deviation, skewness and kurtosis) are used to measure the shadow. This shows that the asymmetries in shadows and in non-shadows are different and good cues for locating shadows. This odd order statistic is also found to be useful in extracting reflectance and gloss from natural scenes.

The *shadow invariant features* chosen for shadow analysis are given as follows:

- *Gradient Similarity:* In the image-formation, transforming the image with a pixel-wise log transformation makes the shadow an additive offset to the pixel values in the scene. To capture this cue, measure the similarity between the distributions of a set of first order derivative of Gaussian filters in neighboring segments of the image. This similarity is computed using the L1 norm of the difference between histograms of gradient values from neighboring segments.
- *Texture Similarity:* It is observed that the textural properties of surfaces change little across shadow boundaries. The textural properties of an image region are measured using the method with a bank of Gaussian derivative filters consisting of 8 orientations and 3 scales and then clustering is applied to form 128 discrete centers. The primary difference is that distortion artifacts in the darker portions of the image and which lead to a slight increase in the number of lower-index textons. They are indicated by more blue pixels.

III. COLOR SPACES USED

Given the illumination changes, the color invariance properties of color histograms can be analyzed. A color histogram depicts the color distribution of the objects in a specific color space, e.g., RGB, HSV, HIS etc. [16]. Therefore, the color constancy of color spaces determines the color invariance properties of color histograms. This section, describe different types of color spaces.

1. *RGB space*

The RGB color space has three channels: red, green, and blue. A histogram can be derived by calculating the number of pixels that have colors in a fixed range which depends on the number of bins. The RGB histogram has no illumination invariance properties [17].

2. *Lab Space*

The LAB space has been designed in a perceptually uniform space. A system is perceptually uniform if a small perturbation to a component value is approximately equally perceptible across the range of that value [18]. In LAB, the L-axis is known as the lightness and extends from 0 (black) to 100 (white).

$$L = \begin{cases} 25[100\,Y/Y_0]^{1/3} - 16 \text{ if } Y/Y_0 \ \geq 0.08856 \\ 903.3\ \frac{Y}{Y_0} \qquad\qquad \text{otherwise} \end{cases} \tag{1}$$

3. Opponent space

The Opponent color space is defined by [19]:

$$[o_1, o_2, o_3] = \left[\frac{R-G}{\sqrt{2}}, \frac{R+G-2B}{\sqrt{6}}, \frac{R+G-B}{\sqrt{3}}\right] \tag{2}$$

The channels $o_1 and\ o_2$ are invariant to light intensity shift, which can be proved by:

$$[o_1, o_2] = \left[\frac{R^C+G^C}{\sqrt{2}}, \frac{R^C+G^C+B^C}{\sqrt{6}}\right] \tag{3}$$

The third channel o_3 has no invariance properties, so we use o_1 and o_2 channels in the experiment.

4. $C_1C_2C_3$ Color System

The $C_1C_2C_3$ Color Space is introduced in [20]. This color space is referred as being invariant to shadows and shading. The conversion from RGB color space is as follows:

$$c_1 = \arctan(R/\max(G,B)),$$
$$c_2 = \arctan(G/\max(G,B)),$$
$$c_3 = \arctan(B/\max(G,B)) \tag{4}$$

5. HSV Color Space

In HSV color space, the convention from RGB color space is obtained as follows [21]:

$$H = \cos^{-1}\left(\frac{0.5\times(R-G)+(R-B)}{\sqrt{((R-G)^2+(R-B)\times(G-B))}}\right),$$
$$S = \frac{\max(R+G+B)-\min(R+G+B)}{\max(R+G+B)},$$
$$V=\max(R+G+B) \tag{5}$$

6. nRGB Color Space

The nRGB color space is the normalized RGB color space [22]:

$$[nR, nG, nB] = \left[\frac{R}{R+G+B}, \frac{G}{R+G+B}, \frac{B}{R+G+B},\right] \tag{6}$$

The nRGB histogram is invariant to light intensity change. Since the $nB = 1 - nR - nG$, we only use $nR\ and\ nG$ channels in the experiment.

7. Transformed Color Space

The invariants to light color change and shift can be achieved by normalizing the pixel value distribution [15]:

$$[T_1, T_2, T_3] = \left[\frac{R-\mu_R}{\sigma_R}, \frac{G-\mu_G}{\sigma_G}, \frac{B-\mu_B}{\sigma_B}\right] \tag{7}$$

where $\mu_i\ and\ \sigma_R$ are the estimated mean and standard derivations of the channel i on the region of interest. After the normalization, the color distribution of each channel is a normal distribution $N(0,1)$, so the Transformed histogram is invariant to light color change and shift. A hybrid shadow detection [23] using above features is evaluated in different color spaces, with bench mark datasets.

IV. 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. We investigate how many pixels are classified properly by the different color spaces. Denote the number of correctly identified foreground pixels of the evaluation sequence 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, we define the *Recall (R)* and *Precision (P)* rates of foreground detection [5]:

$$Recall{:}\ R = \frac{T_F}{T_F+M_F}\ , Precision{:}\ P = \frac{T_F}{T_F+M_S} \tag{8}$$

For optimized parameters, we plot the corresponding Precision and Recall values regarding the bench mark test sequences. We can observe that the $T_1T_2T_3$ produce the best results in both cases. In the indoor scene, though some color space segmentations are the least effective, the performance of the chrominance spaces is the poorest. In the further tests, we will use the *F*-measure [24] which combines recall and precision in a single efficiency measure:

$$F = \frac{2.R.P}{R+P} \tag{9}$$

The figure 3 shows the results for frames of each test sequence using different color spaces: grayscale, $T_1T_2T_3$, HSV, RGB, L*a*b, $O_1O_2O_3$ and $C_1C_2C_3$. We can observe that the $T_1T_2T_3$, space outperforms significantly the other ones, while it is very poor in cases of sharp shadows. The proposed $T_1T_2T_3$, model removes these artifacts with the other color spaces.

TABLE 1. SURVEY ON COLOR SPACE – SHADOW DOMAIN [5]

Methods	Color space	Outdoor / Indoor tests	Number of parameters/ color channels
vallaro	Rg	Both	Invariant
Salvador	$C_1C_2C_3$	Both	invariant
Paragios	Rg	Indoor	Invariant
Mikic	RGB	Outdoor	1
Rittscher	Grayscale	Outdoor	2
Wanget	grayscale	Indoor	2
Cucchiara	HSV	Both	1,33
Martel-Birsson	CIE L *u*v*	Indoor	2
Rautianinen	CIE L*a*b*/HSV	Outdoor	N. a
Siala	RGB	Outdoor	N .a
Proposed	All from above + $T_1T_2T_3$	Both	2

TABLE 2. SHADOW DETECTION ACCURACY OF COLOR SPACES

Dataset/ Color space	CVC	PETS	Hallway	Lab	Caviar
RGB	84.50	83.42	90.14	82.76	80.53
L*a*b	90.32	78.79	92.01	87.23	81.84
$O_1 O_2 O_3$	88.31	79.99	91.89	88.27	85.96
$C_1C_2C_3$	84.62	83.41	92.91	86.49	78.59
HSV	90.47	90.02	92.33	88.98	85.82
nrgb	90.12	91.48	95.41	89.19	86.83
$T_1T_2T_3$	94.42	91.34	97.42	96.10	89.02

TABLE 3:
QUANTITATIVE EVALAUTION OF SHADOW DETECTION AND DISCRIMINATION RATE (COLOR SYSTEM BASED)

Color Model	Detection Shadow	Non-Shadow Dc_n(%)	Discrimination Shadow Dr_s(%)	Non-Shadow Dc_n(%)
HSV	89.9	85.7	93.9	92.4
HIS	89.6	86.6	93.3	87.8
LAB	88.8	78.3	91.5	88.0
$O_1O_2O_3$	95.6	94.4	92.2	98.8
YC_bC_r	91.5	93.2	91.2	97.5
$C_1C_2C_3$	69.5	88.5	87.9	56.0
nrgb	79.2	85.1	81.8	82.0
RGB	88.1	96.6	89.1	99.4
$T_1T_2T_3$	94.9	99.0	94.2	99.3

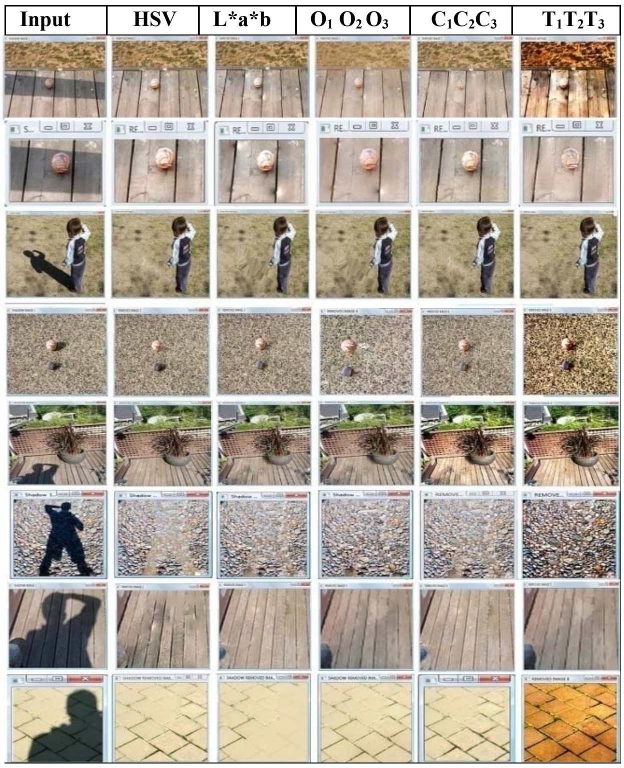

Fig. 1. Qualitative Performance of Color Spaces

The ability to discriminate foreground and shadowed pixels is measured purely. Therefore, the numerical results are considered to be more relevant to compare the capabilities of the color spaces for shadow separation [22]. However, the experiments of this section confirm that appropriate color space selection is crucial in the object detection applications where shadows are insignificant and the $T_1T_2T_3$ space is preferred for this task over other color spaces.

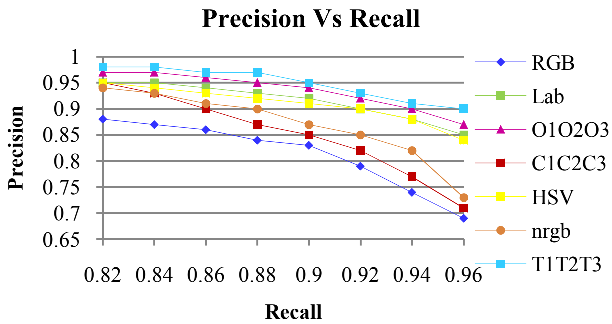

Fig. 2. PR Curves for Different Color Spaces

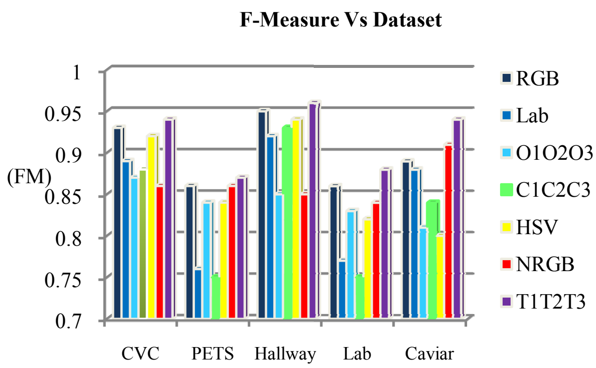

Fig.3. Evaluation of F-Measure for Different datasets

V. CONCLUSION

This paper examines the color space selection for shadow detection. A model framework is developed for this task, which can work with different color spaces. Mean-while, the model can detect shadows under significantly different scene conditions. In our case, the transition between the background and shadow domains is described by statistical distributions of different features. With this model, several well known color spaces are compared, and observed that the appropriate color space selection is an important issue regarding the segmentation results. The method is validated on well-known benchmark datasets of indoor and outdoor shots, which contain both dark and light shadows. Experimental results show that T1T2T3 color space is the most efficient in comparison with other color spaces.

REFERENCES

[1] Liu, Guoliang, *Bayes Filters with Improved Measurements for Visual Object Tracking*, Niedersächsische Staats-und Universitätsbibliothek Göttingen, 2012.

[2] Ning, Jifeng, Lei Zhang, David Zhang, and Chengke Wu. "Robust object tracking using joint color-texture histogram." *International Journal of Pattern Recognition and Artificial Intelligence* 23, no. 07 (2009): 1245-1263.

[3] Godec, Martin, Peter M. Roth, and Horst Bischof. "Hough-based tracking of non-rigid objects", *Computer Vision and Image Understanding* (2012).

[4] Gong, Han, Darren Cosker, Chuan Li, and Matthew Brown. "User-aided single image shadow removal." In *2013 IEEE International Conference on Multimedia and Expo (ICME)*. University of Bath, 2013.

[5] Benedek, Csaba, and Tamás Szirányi. "Study on color space selection for detecting cast shadows in video surveillance." *International Journal of Imaging Systems and Technology* 17, no. 3 (2007): 190-201.

[6] Prati, Andrea, Ivana Mikic, Mohan M. Trivedi, and Rita Cucchiara. "Detecting moving shadows: algorithms and evaluation." *Pattern Analysis and Machine Intelligence, IEEE Transactions on* 25, no. 7 (2003): 918-923.

[7] E. A. Khan and E. Reinhard, Evaluation of Color Spaces for Edge Classification in Outdoor Scenes, *IEEE International Conference on Image Processing*, Genova, Italy, September 11-14, 2005.

[8] D. Marr Vision, A Computational Investigation into the Human Representation of Visual Information, Freeman, New York, 1982.

[9] Subramanyam Muthukumar , Subban Ravi, Nallaperumal Krishnan and P. Pasupathi (2013): Real Time Insignificant Shadow detection for Natural Sceneries, *Recent Advances in Intelligent Systems and Computing, Informatics*, Vol. 235, Aug. 2013, pp. 391-399, Springer, LNAI, Switzerland, DoI: 10.1007/978-3-319-01778-5_40, ISBN: 978-3-319-01778-5

[10] Benedek, et al., Bayesian foreground and shadow detection in uncertain frame rate surveillance videos., IEEE Transactions on Image Processing 17.4 (2008): 608-621.

[11] Zhu J, et al., Learning to recognize shadows in monochromatic natural images, In CVPR 2010, IEEE, pp. 223–230.

[12] Tappen, Marshall, and Jiejie Zhu. "Systems and Methods for Automatically Identifying Shadows in Images." U.S. Patent 20,120,213,440, issued August 23, 2012.

[13] Pizarro, Daniel, and Adrien Bartoli. "Shadow resistant direct image registration." In Image Analysis, pp. 928-937. Springer Berlin Heidelberg, 2007.

[14] Drew, Mark S., Jie Wei, and Ze-Nian Li. "On illumination invariance in color object recognition." *Pattern Recognition* 31, no. 8 (1998): 1077-1087.

[15] Van De Sande, Koen EA, Theo Gevers, and Cees GM Snoek. "Evaluating color descriptors for object and scene recognition." *Pattern Analysis and Machine Intelligence, IEEE Transactions on* 32, no. 9 (2010): 1582-1596.

[16] Rautiainen, Mika, and Timo Ojala. "Color Correlograms in Image and Video Retrieval." In *10th Finnish Artificial Intelligence Conference*, pp. 203-212. 2002.

[17] Reinhard, Erik, Michael Adhikhmin, Bruce Gooch, and Peter Shirley. "Color transfer between images." *Computer Graphics and Applications, IEEE* 21, no. 5 (2001): 34-41.

[18] Chen, Ying, Pengwei Hao, and Anrong Dang. "Optimal transform in perceptually uniform color space and its application in image coding." In *Image Analysis and Recognition*, pp. 269-276. Springer Berlin Heidelberg, 2004.

[19] Swain, Michael J., and Dana H. Ballard. "Color indexing." *International journal of computer vision* 7, no. 1 (1991): 11-32.

[20] Takahashi, et.al., Effect of light adaptation on the perceptual red-green and yellow-blue opponent-color responses, *JOSA* A 2.5 (1985): 705-712.

[21] Ford, Adrian, and Alan Roberts. "Colour space conversions." *Westminster University, London* 1998 (1998): 1-31.

[22] Sun, Da-Wen, ed. *Computer vision technology for food quality evaluation*. Academic Press, 2011.

[23] Muthukumar, S., N. Krishnan, K. Tulasi Nachiyar, P. Pasupathi, and S. Deepa. "Fuzzy information system based on image segmentation by using shadow detection." In *Computational Intelligence and Computing Research (ICCIC), 2010 IEEE International Conference on*, pp. 1-6. IEEE, 2010.

[24] Benedek, Csaba. "Novel Markovian Change Detection Models in Computer Vision." (2008).