Advanced Science and Technology Letters
Vol.122 (IRTT 2016), pp.240-246
http://dx.doi.org/10.14257/astl.2016.122.46

Moving Shadows Removal using HSV Color Space and Texture Analysis

Yangyang Hu , Bingshu Wang, Ying Wang, Yong Zhao[1]

School of Electronic and Computer Engineering, Shenzhen Graduate School of Peking University, Shenzhen, China.
{yangyanghu,wangbingshu,wangying}@sz.pku.edu.cn,
zhaoyong@pkusz.edu.cn

Abstract. The paper presents a new approach for detection of moving shadows. The approach is based on the assumption that shadow regions are darker than the corresponding background but have the same chromacity and texture. We use both HSV and RGB color spaces to extract spectral information and combine two texture features to detect moving cast shadows. Firstly, candidate shadow regions are extracted by spectral analysis. Secondly, we use proposed extended Local Ternary Pattern in the paper, improved edge information, and HSV color space analysis to attain three shadow detectors which are used to vote to select the final shadows, respectively. Our approach is much more effective than other five typical algorithms according to the experimental results.

Keywords: Moving shadows, HSV color space, candidate shadow, extended Local Ternary Pattern.

1 Introduction

The detection and tracking of moving objects is the key point of the surveillance videos applications. Current tracking algorithms typically require that the foreground to be tracked are segmented from the background. However, the cast shadows are frequently misclassified into part of the foreground, because the cast shadows on the ground usually change the intensity of the background pixels significantly. The detection methods would be disturbed by the shadows.

Shadows are always coupled with the objects casting them and may have the similar size as the actual objects [1]. Cast shadows bring serious problems while misclassifying the shadow points as foreground and distort the true shape of the objects, they also change the color component of the foreground objects. So, a shadow removal procedure is necessary to improve the object detection accuracy.

During the past years, researchers have proposed many methods to detect cast shadows, in literature [2], shadow detection algorithms were divided into five categories: chromacity [3], physical [4], geometry [5], small region texture [1], and large region texture methods [6]. We also use these five methods for comparison.

[1] Yong Zhao is the corresponding author.

ISSN: 2287-1233 ASTL

Chromacity-based method assumes that regions under cast shadow have a lower intensity but retain the same chromacity as original regions. So a color space with better separation between intensity and chromacity than RGB color space is needed. Physical method attempts to model the specific appearance of shadow pixels. Geometry-based method predicts the orientation, size and shape of the shadows with proper knowledge of the light source, the object shape and the ground plane. Small region (SR) texture-based method identifies candidate shadow regions or pixels by intensity and then classifies the candidate regions or pixels into foreground or shadow based on texture correlation. Large region (LR) texture-based method uses color features to create large candidate shadow regions and then using gradient-based texture correlation to distinguish them from real objects. Each method takes use of single property, which can achieves good discrimination in particular scene. The method proposed in this paper uses both chromacity and texture features to adapt various scenes.

2 Cast Shadow Removal Method

The method proposed in this literature uses chromacity, edge features and texture features to achieve high shadow detection and discrimination rates. The flow diagram of the method is illuminated in Figure 1.

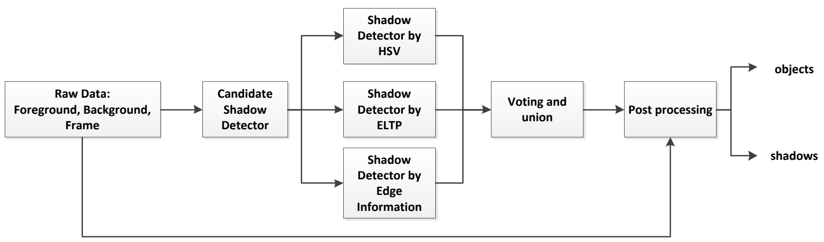

Fig. 1. Flow diagram of the proposed method.

2.1 Candidate Shadow Detector by Spectral Analysis

We compare the intensity of pixels between the given frame and background, and those pixels darker than the background generate the basic candidate shadows. The mathematical expressions are as equation (1) and (2).

$$f_r = \frac{F_g/B_g}{F_b/B_b}, \quad f_g = \frac{F_r/B_r}{F_b/B_b}, \quad f_b = \frac{F_r/B_r}{F_g/B_g} \tag{1}$$

$$CandidateShadow = \begin{cases} 1 & if \ |f_i - \mu_i| < \lambda, \ i\epsilon\{r,g,b\} \\ 0 & others \end{cases} \tag{2}$$

Where F_i and B_i $(i\epsilon\{r,g,b\})$ represent the color component of current frame pixels and background frame pixels, respectively. The f_i represents spectral ratio, μ_i equals to 1 in the ideal situation and λ is a small value.

2.2 Shadow Detector by HSV Approach

HSV color space provides a natural separation between chromacity and brightness. Considering that a shadow cast on background does not change its hue (H), we regard a pixel in the candidate shadow regions as a part of a shadow if the hue of the pixel is almost invariable and the following conditions should be satisfied:

$$\frac{\sum_i^n (F_i^S - B_i^S)}{n} \le \tau_S \tag{3}$$

$$\frac{\sum_i^n |F_i^H - B_i^H|}{n} \le \tau_H \tag{4}$$

where F_i^C and B_i^C represent the saturation (S) and hue (H) values of HSV for the pixel point i in the frame (F) and background reference image (B), respectively. τ_S and τ_H represent the empirical thresholds that vary from scene to scene.

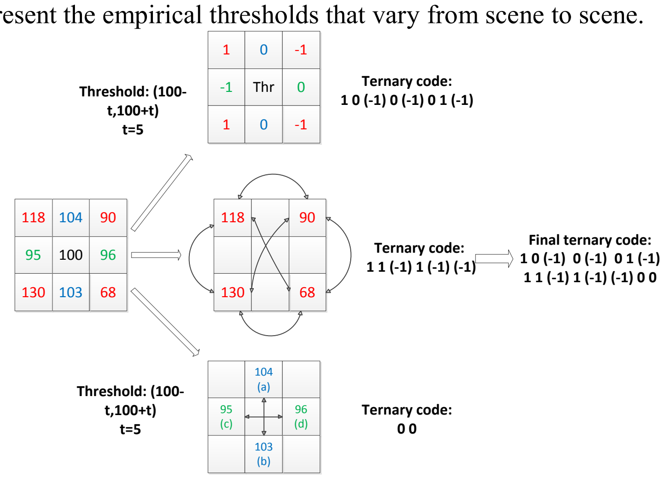

Fig. 2. ExLTP for shadow detection.

2.3 Shadow Detector by ExLTP

The Local Ternary Pattern (LTP) [7] extended the LBP to ternary code to address the problem of sensitive to noise. We propose an extended Local Ternary Pattern (ExLTP) operator to enhance the integrity of local texture pattern. The coding procedure of the ExLTP is illustrated in Figure. 2.

In a 3×3 neighborhood, for a single channel, we consider the central pixel as threshold and each pixel is compared with it, then the four vertexes of mesh compare with each other, respectively. And we compare pixel on position a with that on b, and c with d, as show in Figure. 2. Finally, we get a 48-value (16*3) for the three channels of RGB for each pixel.

2.4 Shadow Detector by Edge Information

A method using edge information to extract shadow regions is proposed. Candidate shadow pixels are extracted using intensity and saturation features in the HSV color space as in Section 2.2 with a different threshold to ensure high detection accuracy. The connected components of shadow pixels are regarded as candidate shadow regions. We split regions using Canny edge detector to detect edges that occur in the foreground but not in the background.

2.5 Union of Detectors and Post-approach

A voting mechanism is employed to decide which pixels form the shadows. A pixel will be regard as shadow pixel if it is detected as shadow pixel by no less than two of the shadow detectors mentioned above. Morphological open/close operation and small holes filling are implemented to get the final shadow regions.

3 Experimental Results

3.1 Datasets and Evaluation Metrics

The datasets come from [8] and CDW-2012 datasets [9]. Five sequences and scenes which include typical indoor and outdoor scenes were chosen to evaluate our method and comparisons. And the evaluation metrics are as follows:

$$\eta = \frac{TP_S}{T_S + FN_S} \tag{5}$$

$$\xi = \frac{TP_F}{TP_F + FN_F} \tag{6}$$

$$\theta = \frac{2\eta\xi}{\eta + \xi} \tag{7}$$

where TP and FN stand for the true positive and false negative pixels with respect to shadows (S) or foreground objects (F). The shadow detection rate (η) and shadow discrimination rate (ξ) proposed by Prati et al. [8] are metrics that widely used to evaluate the performance of shadow detection methods. And θ is the comprehensive evaluate metric.

3.2 Qualitative and Quantitative Results

Qualitative results of five sequences are given in Figure. 3. We set a same set of parameters: $\tau_S = 40, \tau_H = 48, and\ \delta = 158$ for both indoor and outdoor scenes.

As is shown in Table 1 and Figure 4, the results of the proposed method are better than the compared methods for most scenes. We get the highest rates of shadow detection in all scenes. The comprehensive detection rate increases by 6% on average, compared with suboptimal results. In the scene of Highway1, our method is slightly

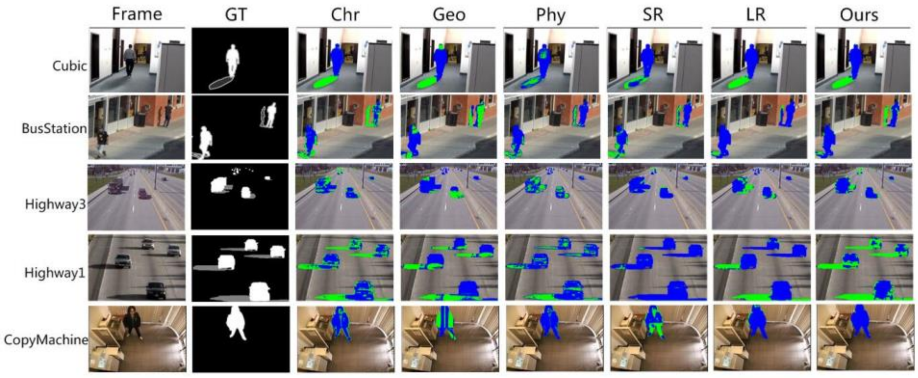

Fig. 3. Qualitative shadow detection results.

Table 1. The comprehensive detection rate (θ) measure evaluation of six methods in different scenes.

	busStation	**copyMachine**	**cubicle**	**Highway1**	**Highway3**
Chromacity	0.6922	0.7628	0.6729	0.7036	0.5340
Geography	0.4989	0.4761	0.6160	0.7055	0.5461
Physical	0.3680	0.3854	0.3071	0.5679	0.4879
SR	0.6159	0.5820	0.4314	0.2868	0.1085
LR	0.1363	0.2959	0.4772	**0.7404**	0.5356
ours	**0.7580**	**0.8050**	**0.7654**	0.7264	**0.6590**

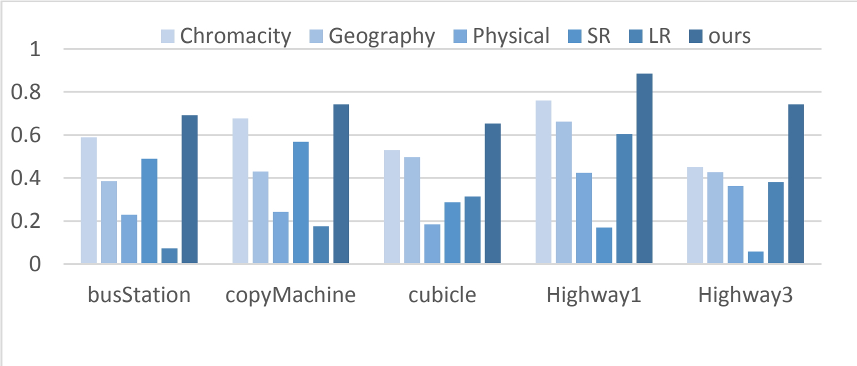

Fig. 4. The shadow detection rate (η) measure evaluation of six methods in different scenes.

worse than the LR based method but still better than others. The main reason is the lack of chromacity and texture information in outdoor scenarios. Some pixels at the edges of the objects are easily misclassified into shadows. The results of indoor scenes are better than outdoor scenes, owing to the abundance of chromacity and texture features.

4 Conclusion

In this paper, we propose a method using both RGB and HSV color spaces analysis methods combined with texture feature and edge feature innovatively to detect cast shadows. Based on three detectors of HSV, ExLTP and Edge, a voting strategy is adopted to obtain the final cast shadow regions.

Experimental results of both indoor and outdoor scenes demonstrate that our method achieve a higher shadow detection rate than the compared methods. For all test sequences, we obtain a 6% improvement of comprehensive detection rate on average, compared with the suboptimal results. Especially, our method is no less than 11.3% higher than any other methods for the scene of Highway3. However, as pixels at the edges of objects are easily misclassified into shadows under the strong light condition, much more works need to be done in the future, and parameters can be optimized for specific scenarios.

References

1. Al-Najdawi, N., Bez, H.E., Singhai, J., Edirisinghe, E. A.: A Survey of Cast Shadow Detection Algorithms. J. Pattern Recognition Letters. 33(6), 752--764(2012)
2. A. Prati, I. Mikic, M. Trivedi, R. Cucchiara.: Detecting moving shadows: algorithms and evaluation. IEEE Transactions on Pattern Analysis and Machine Intelligence. 25 (7), 918--923(2003)

3. Huang, J.B., Chen, C.S.: Moving Cast Shadow Detection Using PhysicsBased Features. In: 2009 IEEE Conference Computer on Vision and Pattern Recognition, pp. 2310--2317. IEEE Press, New York(2009)
4. Hsieh, J.W., Hu, W.F., Chang, C.J., Chen, Y.S.: Shadow Elimination for Effective Moving Object Detection by Gaussian Shadow Modeling. J. Image and Vision Computing. 21(3), 505--516(2003)
5. Leone, A., Distante, C., Buccolieri, F.: Shadow Detection for Moving Objects Based on Texture Analysis. J. Pattern Recognition. 40(4), 1222--1233(2007)
6. Sanin, A., Sanderson, C., Lovell, B.C.: Improved Shadow Removal for Robust Person Tracking in Surveillance Scenarios. In: IEEE 20th International Conference on Pattern Recognition, pp. 141--144. IEEE Press, New York(2010)
7. Tan, X., Triggs, B.: Enhanced Local Texture Feature Sets for Face Recognition under Difficult Lighting Conditions. J. IEEE Trans. Image Processing. 19(6), 1635--1650(2010)
8. Xu D, Li X, Liu Z, et al.: Cast shadow detection in video segmentation. J. Pattern Recognition Letters. 26(1), 91--99(2005)
9. A video database for testing change detection algorithms, http://wordpress-jodoin.dmi.usherb.ca/dataset2012/