Optics & Laser Technology 54 (2013) 232–241

Contents lists available at ScienceDirect

Optics & Laser Technology

journal homepage: www.elsevier.com/locate/optlastec

Robust and accurate moving shadow detection based on multiple features fusion

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ARTICLE INFO

Article history:
Received 14 December 2012
Received in revised form
21 May 2013
Accepted 30 May 2013
Available online 26 June 2013

Keywords:
Shadow detection
Object segmentation
Feature fusion

ABSTRACT

In recent years, moving cast shadow detection has been becoming a critical challenge to improve the accuracy of moving object detection in video surveillance. In this paper, we derive a robust moving cast shadow detection method based on multiple features fusion. Firstly, several kinds of features such as intensity, color and texture are extracted sufficiently by means of various measures for the foreground image. Then, the synthetic feature map is generated by linear combination of these features. Consequently, moving cast shadow pixels are distinguished from their moving objects roughly. Finally, spatial adjustment is applied to correct misclassified pixels for acquiring the refined shadow detection result. The effectiveness of our proposed method is evaluated on various scenes. The results demonstrate that the method can achieve high detection rate. In particular, the experiments also indicate that it significantly outperforms several state-of-the-art methods by extensive comparisons.

1. Introduction

Moving object detection is a fundamental and critical task in many applications such as object tracking, object recognition, video surveillance, video compression and so forth. Background subtraction is one of the common approaches for detecting moving objects. However, cast shadows always move with their corresponding objects such that many background subtraction methods cannot separate them accurately. The inaccurate separation might lead to object merging, object shape distortion, and even object losses. Therefore, detecting and eliminating shadow regions are highly desirable and necessary in video processing and motion analysis fields.

Many efficient methods have been put forward to detect moving shadows in recent years. In general, existing shadow detection methods can be classified into four categories based on several features [1]: chromaticity, physical, geometry and textures.

Chromaticity-based methods take advantage of the assumption that shadow regions are darker but almost maintain their chromaticity invariant. For better separation between intensity and chromaticity, several color space such as HSV [2], $c_1c_2c_3$ [3], HSL [4], RGB [5–8], or a combination of them [9] have been developed to detect moving cast shadow robustly. Cucchiara et al. [2] exploited color information in HSV color space for shadow detection to improve object segmentation. They proved that cast shadows were darker than the corresponding background in luminance component, while hue and saturation components were consisted with the corresponding background and changed within a certain range experimentally. Salvador et al. [3] described an efficient method to segment cast shadow in both still images and video sequences, which verified the invariant $c_1c_2c_3$ color and geometric properties of shadows. Grest et al. [4] discussed a similarity measure in HSL color space to separate color from intensity information, which improved the quality of shadow removal significantly. Hypothesizing that RGB ratios were constants, Song et al. [6] constructed a color ratio model followed Gaussian distribution to determine whether a pixel belonged to shadows or not in traffic images. Amato et al. [7] employed local color constancy property to detect both achromatic and chromatic shadows from foreground accurately. Choi et al. [8] proposed an adaptive shadow elimination method using cascading chromaticity difference estimator, brightness difference estimator and local relation estimator, which could be adapted to variations of illumination and environment. To be complementary with each other efficiently, Sun et al. [9] utilized the combined models in both HSI and $c_1c_2c_3$ color spaces to distinguish shadows from foreground regions. As mentioned above, most of these methods are simple to implement and computationally inexpensive.

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http://dx.doi.org/10.1016/j.optlastec.2013.05.033

However, they are sensitive to noise and will fail when shadow regions are darker or moving objects have similar color information with background.

Nadimi et al. [10] presented a physical-based model on a spatio-temporal albedo test and dichromatic reflection model for moving cast shadow detection. They focused on outdoor scenes and incorporated multiple sources with different spectral power distributions. Martel-Brisson et al. [11] described a pixel-based statistical approach to model and detect moving cast shadows by parameterizing probability density functions. Over restrictive probabilistic models, Joshi et al. [12] introduced a semi-supervised learning technique with color and edge characteristics to identify shadows, which was implemented by Support Vector Machines (SVMs) and co-training algorithms on a small set of human-labeled data. Physical methods can adapt automatically to complex scene conditions but need update shadow models timely and user interactions.

Geometry-based methods are designed with the predicted orientation, size and even shape of shadows by proper prior knowledge of the illumination source, camera location and object geometry to detect moving shadows. For eliminating unwanted pedestrian-like shadows, Hsieh et al. [13] proposed a Gaussian shadow model via parameterizing with several features including the orientation, mean intensity, and center position of one shadow region. For exploiting spectral and geometrical properties of shadows, and the relationship between points in shadow region and space position and vehicle shape, Fang et al. [14] presented a moving vehicle cast shadow detection method, which was carried out by occluding function using 1D wavelet transform. Geometric-based methods do not rely on the background reference but need more prior knowledge and scene limitations.

Generally, texture-based shadow detection methods hypothesize that background image has similar texture with shadow regions while different textures with moving objects. Leone et al. [15] proposed a moving cast shadows method based on Gabor functions and matching pursuit strategy. Zhang et al. [16] first employed ratio edge as the ratio between the intensity of one pixel and its neighboring pixels to detect shadows. The experiment results proved it was illumination invariant. Confirming the existance of shadows, Xiao et al. [17] reconstructed coarse object shapes, and then extracted cast shadows by subtracting moving objects from one changed mask. By creating one mask of candidate shadow pixels using chromaticity information, Sanin et al. [18] discriminated cast shadows from moving objects by means of gradient information. Bullkich et al. [19] assumed nonlinear tone mapping between shadows and their corresponding background, and analyzed the structural content by Tone Mapping to separate shadows from suspected foregrounds. Meher and Murty [20] applied a statistical method called principal component analysis (PCA) to obtain the search directions for moving shadow regions and then utilized the variance of regions to test the homogeneity for separating shadow regions from vehicle regions. Methods based on texture similarity are independent of color information, and against illumination changes. However, they will be failure when moving objects and shadow regions possess similar texture information with corresponding background regions.

As mentioned above, methods based on only a single feature might lead to misclassification for moving cast shadows. Recently, multiple features fusion is becoming an active research area and exhibits a significant trade-off among features [21–27]. Grouping potential shadows into partitions in terms of a bluish effect and edge, Huerta et al. [22] analyzed temporal and spatial similarities for all these regions in order to detect umbra shadows. Lin et al. [23] presented a moving shadow removal algorithm by combining texture and statistical models, which was realized via edge information and gray level-based feature modeled with Gaussian. HAMAD et al. [24] employed both color and texture information to identify cast shadow regions. They utilized intensity ratio and entropy to characterize the two features. Boroujeni et al. [25] proposed a semi-supervised classification method based on hierarchical mixture of MLP experts to detect moving cast shadows. They constructed feature vectors including color intensity, average illumination, color distortion and light distortion to demonstrate environmental properties of frames. McFeely et al. [26] adopted the combination of color illumination invariance and texture analysis to identify shadows after tree-structured segmentation for digital imagery. Dai et al. [27] exploited color information in HSV color space, texture similarity by LBP and local variance to detect moving cast shadows. Although the fusion of various features was adopted in many works, different measures for the same type of features are not considered significantly. Additionally, most of those methods detected shadow pixels in serial mode rather than in parallel.

Inspired of the existing methods, we propose a novel moving cast shadow detection method based on feature fusion. Instead of using one single feature or more features sequentially, three types of features are taken into account simultaneously in our work. First, intensity, color and texture features are extracted for one foreground image. In order to characterize these features comprehensively as much as possible, we represent color information in terms of multiple color spaces and multi-scale images. Meanwhile, texture information is described by entropy and local binary patterns. Second, a feature map corresponding to the foreground is generated by fusing these features. Subsequently, moving cast shadows can be identified roughly from their moving objects in terms of the feature map. At last, in order to obtain the refined shadow detection result, spatial adjustment is carried out to modify the misclassified pixels. Extensive experiments and comparable results demonstrate that the proposed method exhibits excellent performance and outperforms several well-known methods.

This paper is organized as follows. Section 2 presents the proposed shadow detection method, which consists of foreground segmentation, feature extraction, feature fusion for shadow detection and spatial adjustment. Section 3 analyzes the experiments and conclusions are given in Section 4.

2. The proposed shadow detection method

Shadows appear when objects partially or totally occlude direct light from a source of illumination. Shadows can be classified into two classes: self-shadow and cast shadow. The former occurs in the part of an object which is not illuminated by direct light. The latter is the area projected by the object in direct light. In particular, the latter is called moving cast shadow if the object is moving.

In this section, we present a multiple feature fusion method for robust shadow detection, called MFF. Without loss of generality, the proposed method is based on assumptions that shadow regions are darker but retain similar chromaticity and texture information with respect to background regions. Fig. 1 shows the flowchart of the proposed method including foreground segmentation, feature extraction, feature fusion and spatial adjustment.

2.1. Foreground segmentation

Foreground extraction is very necessary prior to moving cast shadow detection, which can reduce computation time and improve detection accuracy. For the sake of simplicity, the analyzed video sequences are assumed to be captured in a still camera environment. In our study, Gaussian Mixture Model (GMM) [28] is