ARTICLE IN PRESS
JID: CAEE [m3Gsc;December 22, 2017;0:37]

Computers and Electrical Engineering 000 (2017) 1–13

Contents lists available at ScienceDirect

Computers and Electrical Engineering

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

Automatic removal of complex shadows from indoor videos using transfer learning and dynamic thresholding[☆]

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ARTICLE INFO

Article history:
Received 11 September 2017
Revised 11 December 2017
Accepted 12 December 2017
Available online xxx

Keywords:
Shadow removal
Transfer learning
Thresholding
Video analysis
Video surveillance

ABSTRACT

In video-based tracking and recognition applications, shadows are usually mis-classified as foreground or part of it due to its close associative to the objects. Shadows in indoor scenarios are more challenging and usually characterized by multiple light sources that produce complex patterns. In this article, we present a learning-based method for removing shadows. Our method suppresses light shadows with a dynamically computed threshold and removes dark shadows using an online learning strategy that is fine-tuned with the automatically identified examples in the new videos. Our experiments demonstrate that the proposed method adapts to the videos and remove shadows effectively. The average accuracy exceeds 97%. The sensitivity of shadow detection varies slightly with different confidence levels used in example selection for retraining and high confidence usually yields better performance with less retraining iterations. In the evaluation of efficiency, updating kNN imposes little impact on the processing time.

1. Introduction

Background subtraction is a critical step in many computer vision applications ranging from object tracking to action recognition [1,2], which requires accurate foreground objects. However, the foreground object is usually distorted by non-stationary shadows of the moving object. Due to its nature of dynamically emerging with objects, the shadow is usually misclassified as foreground object or part of it. There have been many methods developed to handle shadow removal in a variety of outdoor scenarios, e.g., traffic monitoring [3] and surveillance [4]. However, these methods are facing difficulties in indoor lighting, where multiple light sources combine to produce complex shadows. Research has been conducted for indoor scenarios [5], in which a manually specified threshold is used.

Shadows in indoor scenarios are usually characterized by multiple light sources. An example is shown in Fig. 1(a), which shows that part of the shadow appears brighter than the others. Without removing the shadow, the foreground object tends to be erroneously segmented, as shown in Fig. 1(b); and with shadow removal, the optimal body silhouette contains no shadow component, as shown in Fig. 1(c). The inconsistent hue and intensity of shadows make automatic removal a challenging task; simple color-based methods are ineffective and could cause the shattered object of interest [5].

☆ Reviews processed and recommended for publication to the Editor-in-Chief by Associate Editor Dr. Gustavo Ramirez Gonzalez.

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https://doi.org/10.1016/j.compeleceng.2017.12.026
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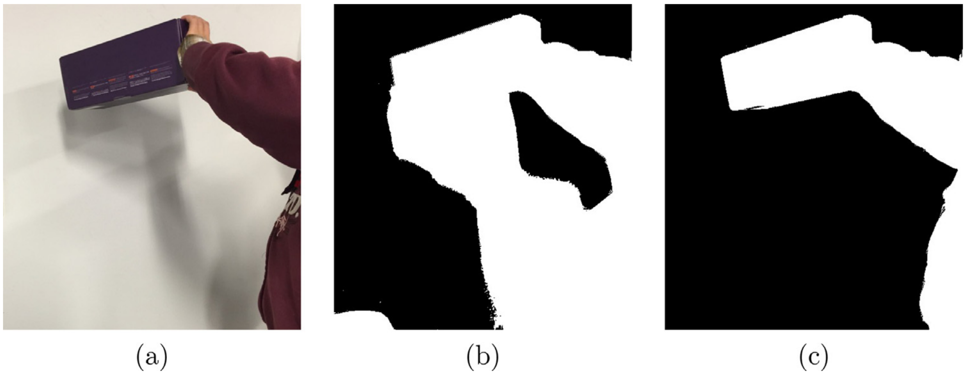

Fig. 1. Complex shadow and the background subtraction results. (a) a frame showing complex shadow of different shades. (b) background subtraction result. (c) background subtraction with shadow removal.

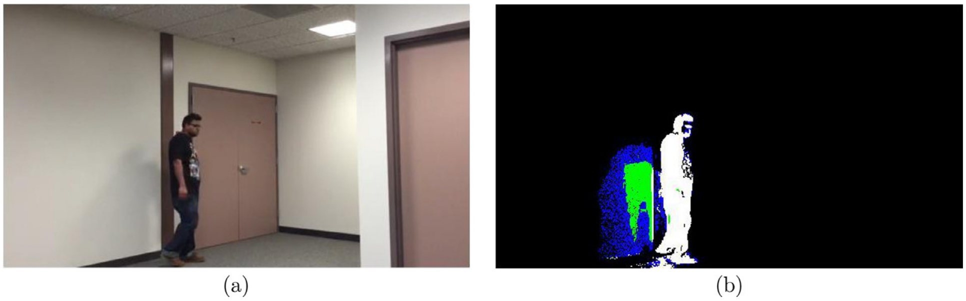

Fig. 2. An example of shadows in an indoor scenario.

In this article, we present a learning-based shadow removal method to suppress shadows in indoor videos that contain complex shadows. Our method categorizes shadows into light shadows and dark shadows based on the color changes with respect to the background model. In dealing with light shadows, chroma of a pixel has little changes but its intensity is slightly reduced. Hence, a threshold is dynamically determined by searching for pixels of the same color but darker in intensity in contrast to the background model. For dark shadows, an online transfer learning-based method is proposed to identify the unwanted regions. A base classifier is initially trained with manually annotated examples and refined with the automatically identified examples in the new videos on-the-fly to adapt to the video under process and to classifier dark shadow pixels.

The rest of this paper is organized as follows: Section 2 presents the related work of shadow removal in videos and, in particular, methods to handle indoor scenarios. Section 3 describes our proposed method in detail. Section 4 discusses the experimental results using several indoor videos. A comparison study is conducted to demonstrate the improvements in our method. Section 5 concludes this paper with a summary and future work.

2. Related work

Shadow removal is a challenging problem in both still images [6] and videos [7]. Although methods that deal with still image can be applied to video frames, their performance degrades and the computational complexity is usually too high for practical applications [8]. To remove shadows from videos, various color models have been explored to characterize their dynamic changes. Cucchiara et al. [9] proposed an HSV color space model for shadow removal from videos. The idea is that shadow changes the hue and the saturation components in a certain range while reduces the brightness. The thresholds are derived from the average image luminance and gradient. Gallego and Pardas [10] implemented a Bayesian method using brightness and color distortion model for shadow removal. Amato et al. [11] developed a method that employs local color constancy. The values of the background image are divided by the values of the current frame in the RGB space. The method assumes that in the luminance ratio space, a low gradient constancy is present in all shadowed regions due to local color constancy. A chroma difference model in RGB space was also developed in [12]. A 3D cone-shaped illumination model was proposed in [13] for background subtraction with shadow removal in indoor surveillance. The work explores the challenges of illumination changes in indoor environments. Gomes et al. [14] integrated color and gradient information with image segmentation using a cascade classifiers. Chromatic and texture features of the foreground objects and their shadows were extracted and classified and a stochastic majority voting scheme was used to detect the shadow regions. Huerta et al. [15] leveraged temporal similarity between textures and spatial similarities between color angle and brightness distor-

Please cite this article as: X. Yuan et al., Automatic removal of complex shadows from indoor videos using transfer learning and dynamic thresholding, Computers and Electrical Engineering (2017), https://doi.org/10.1016/j.compeleceng.2017.12.026