Image and Vision Computing 62 (2017) 19–27

Contents lists available at ScienceDirect

Image and Vision Computing

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

User-assisted image shadow removal☆

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ARTICLE INFO

Article history:
Received 27 November 2015
Received in revised form 29 August 2016
Accepted 6 April 2017
Available online 18 April 2017

Keywords:
Image shadow removal
User-assisted computer vision
Colour correction
Curve fitting
Smoothing

MSC:
68U10
68U05

ABSTRACT

This paper presents a novel user-aided method for texture-preserving shadow removal from single images requiring simple user input. Compared with the state-of-the-art, our algorithm offers the most flexible user interaction to date and produces more accurate and robust shadow removal under thorough quantitative evaluation. Shadow masks are first detected by analysing user specified shadow feature strokes. Sample intensity profiles with variable interval and length around the shadow boundary are detected next, which avoids artefacts raised from uneven boundaries. Texture noise in samples is then removed by applying local group bilateral filtering, and initial sparse shadow scales are estimated by fitting a piecewise curve to intensity samples. The remaining errors in estimated sparse scales are removed by local group smoothing. To relight the image, a dense scale field is produced by in-painting the sparse scales. Finally, a gradual colour correction is applied to remove artefacts due to image post-processing. Using state-of-the-art evaluation data, we quantitatively and qualitatively demonstrate our method to outperform current leading shadow removal methods.

1. Introduction

Shadows are ubiquitous in natural scenes, and their removal is an interesting and important area of research. As well as a motivation to solve this problem for artistic image editing, shadows can affect the performance of many computer vision algorithms. For example, unwanted shadow boundaries can cause artefacts in image segmentation and contribute to drift when tracking given moving objects and scenes.

In this paper, a semi-automatic method is proposed for high-quality shadow removal using user-defined flexible single strokes covering the shadow and lit pixels. Our method sacrifices full autonomy for extremely simple user input, as opposed to existing manual approaches that require fine-scale input, *e.g.* accurate shadow contours. Given detection, our method produces accurate shadow removal optimised for robust penumbra recovery. Using the current state-of-the-art shadow removal ground truth dataset [1], our solution is quantitatively evaluated against other leading methods and demonstrates notably improved performance. Numerous visual comparisons of our method *versus* existing methods are also presented, demonstrating qualitatively more pleasing results. Our approach represents what we believe to be a state of the art technique for shadow removal with a thorough evaluation against the current leading approaches.

1.1. Related work

A shadow generally consists of umbra and penumbra areas. The umbra is the darkest part of the shadow while the penumbra is the wide outer boundary with a gradual intensity change between the umbra and lit areas. The penumbra scale is non-uniform and shadowed surface textures generally become weaker within it. A shadow image I_c^+ can be considered to be a Hadamard product of a shadow scale layer $\mathcal{S}_c$ and a shadow-free image I_c^* as shown in Eq. (1).

$$I_c^+ = I_c^* \circ \mathcal{S}_c \tag{1}$$

For a lit pixel, the illumination is constant in both shadow and shadow-free images. For a shadow pixel, its intensity in a shadow image is lower than its intensity in the shadow-free image. Consequently, the scales $\mathcal{S}_c$ of the lit area are 1 and other areas' scales are between 0 and 1.

☆ This paper has been recommended for acceptance by Seong-Whan Lee, PhD.
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http://dx.doi.org/10.1016/j.imavis.2017.04.001
0262-8856/

However, most images appearing on the Internet are not linear images. These images have commonly been post-processed by some non-linear image processing algorithms such as gamma-correction, JPEG compression, and non-linear filters. After a linear shadow recovery process, contrast artefacts can appear in the shadow areas [2].

Approaches to shadow removal can be categorised as either automatic [1,3-8] or user-aided [2,9-11]. The problem can be broken down into two stages: shadow detection and shadow removal.

Automatic approaches do not require any user interaction but risk inaccurate shadow detection or require special setups for capture which do not work for general images. Intrinsic image based methods are a popular branch of automatic techniques (*e.g.* [3,4]). The decomposition of intrinsic images provides shading and reflectance information but can be unreliable leading to over-processed results. The decomposition is generally based on an assumption that the illumination change is smooth or the reflectances of the scene lie on an illumination-invariant direction. Another branch of techniques are shadow feature learning based methods [1,12-16]. However, detection can be often unreliable due to limited training data and the quality of initial image edge detection and segmentation. Several approaches [12-14,16] detect shadows by classifying edges in images using edge features, *e.g.* intensity, texture, chromaticity and intensity ratio. Graphical models [1,15] can also form the basis of detection. Yao et al. [15] detect shadow by using a reliable graph model and colour features to classify pixels. In their approach, each pixel is a node with encodes node reliability based on strength of shadow feature, and node relationships described using similarity between neighbours. Guo et al. [1] detect shadows by classifying segments in images that adopt similar shadow features and remove shadows using a variant alpha-matting algorithm. Some methods apply additional active light sources to capture shadowless objects, *e.g.*, by comparing images with an illumination source at different positions [5] and comparing flash and no-flash image pairs [6]. However, active lighting restricts the types of scene that shadow removal can be applied to — as using special lighting setups outdoors is often not practical. Other methods adopt optical filters to acquire multi-spectral information to achieve illumination detection, *e.g.* by comparing NIR and RGB images [7] and by comparing RGB and single-colour-filtered images [8], but these methods are generally limited to special scenario cases, *e.g.* sunlight and non-black surfaces.

User-aided methods generally achieve better shadow detection and removal at the cost of user input. Wu et al. [9] require a high degree of user intervention where multiple regions of shadow, lit area, uncertainty and exclusion are identified. They apply a Bayesian optimisation to derive a shadow matte and a shadow-free image. Others [10,11] require fine input defining the shadow boundary. Liu and Gleicher [10] proposed a curve fitting method and a global alignment of gradients to acquire shadow scales but have issues when relighting the umbra and can introduce artefacts at uneven boundaries. Shor and Lischinski [17] detect shadow using image matting from a grown shadow seed. They only require one shadow pixel as input, but have limitations in cases where the other shadowed surfaces are not surrounded by the initially detected surface or when the penumbra is too wide. Arbel and Hel-Or [2] apply a thin-plate model to the intensity surface. They require users to specify multiple texture anchor points to detect the shadow mask but the input overhead increases when shadows are distributed in multiple regions. Su and Chen [11] developed a method to estimate shadow scales using dynamic programming. Their gradient alignment for intensity samples allows for less accurate user inputs compared with Refs. [9,10]. They also provide a healing tool for users to manually amend artefacts in highly-curved shadow boundary segments. Gong and Cosker [18] introduced a fast approach which categorises intensity profiles into several sub-groups and derives the shadow scales for each of them. They require two types of scribbles for marking lit and shadow pixels. Similarly, Zhang et al. [19] require the same user input of Ref. [18]. However, their method requires a shadow matte (guided by the user's scribbles) to identify shadows, which is sensitive to user-scribbles because their image matting is affected by pixel location.

To date, most shadow removal methods [2,9-11,19] have only been evaluated by visual inspection on some selected images — with only a few exceptions performing quantitative evaluation. Guo et al. [1] provided the first public ground truth dataset for shadow removal and perform quantitative testing. However, their error measurement is variant to the size and darkness of shadows and some of their shadow-free ground truth shows inconsistent illumination compared with the lit area of their corresponding shadow images.

1.2. Contributions

Given our overview of state of the art approaches, 3 main contributions are proposed:

1) *Simple user input*: Past work, *e.g.* [2,9-11], requires precise user-input defining the shadow boundary. Our method only requires users to define some single rough strokes covering related shadow and lit pixels — without the need to differentiate between samples in shadow and lit areas.
2) *Intelligent sampling*: Adaptive sampling with variable intervals and lengths is proposed to address shadow boundary artefacts in past work [2,10], which uses fixed intervals and lengths. Unlike past work [2,10,11], unqualified samples are intelligently filtered. These can affect the quality of shadow scale estimation, *e.g.* samples with high noise or sampling lines passing through boundaries caused by occlusions or strong background texture.
3) *Robust scale estimation*: Fast local group processing is proposed for selected samples and initially estimated scales to improve smoothness of shadow removal. Post-processing effects cause inconsistency in shadow corrected areas compared with the lit areas both in tone and contrast. Without introducing chromatic artefacts, colour-safe correction is proposed to amend the scales.

To summarise, the paper presents several solutions to improve shadow removal quality, and these have been quantitatively verified using robust error measurement and the standard dataset in this area [1].

2. User-assisted image shadow removal

In this section, our algorithm is first described in brief before being expanded on with technical details for each of its components. Our algorithm consists of 4 steps (see Fig. 1):

1) *Pre-processing* (Section 2.1) A shadow mask is detected (Fig. 1 (b)) using a KNN classifier trained from K-Means clustered data from user inputs (*e.g.* Fig. 1 (a)). A *fusion image* is generated, which provides an illumination-insensitive layer, by fusing the channels of YCrCb colour space and de-noising (Fig. 1 (c)).
2) *Intensity sampling* (Section 2.2) Intensity profiles are obtained for sampling lines perpendicular to shadow boundaries. *Poor* samples are filtered based on similarity of illumination change (Fig. 1 (d)) and de-noised using directional bilateral filtering (Fig. 1 (e)).