User Aided Approach for Shadow and Ghost Removal in Robust Video Analytics

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Abstract. In almost all computer vision applications moving objects detection is the crucial step for information extraction. Shadows and ghosts will often introduce errors that will certainly effect the performance of computer vision algorithms, such as object detection, tracking and scene understanding. This paper studies various methods for shadows and ghost detection and proposes a novel user-aided approach for texture preserving shadows and ghost removal from surveillance video. The proposed algorithm addresses limitations in uneven shadow and ghost boundary processing and umbra recovery. This approach first identifies an initial shadow/ghost boundary by growing a user specified shadow outline on an illumination-sensitive image. Interval-variable pixel intensity sampling is introduced to eliminate anomalies, raised from unequal boundaries. This approach extracts the initial scale field by applying local group intensity spline fittings around the shadow boundary area. Bad intensity samples are substituted by their nearest intensities based on a log-normal probability distribution of fitting errors. Finally, it uses a gradual colour transfer to correct post-processing anomalies such as gamma correction and lossy compression.

Keywords: Shadow and ghost removal, user-assisted, spline fittings, interval variable.

1 Introduction

A set of connected pixel points detected in motion but not related to any real moving object is called as Ghost. A set of connected background pixel points modified by a shadow cast over them by a moving object is called as Shadow. Shadows and ghosts are ubiquitous in natural scenes, and their removal is an important area of research. Even though there are lot of automatic methods[1,2] available from past work ,they are not matured enough to completely remove shadow/ghost artefacts from images. This paper focuses on user-aided single image shadow and ghost removal. User-aided methods generally provide better shadow/ghost detection and removal at the cost of user given input. According to previous work shadow and ghost effects can be specified as an additive scale fields S_c *and* G_c in the log domain. In this domain, an

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image $\hat{H}_c$ with these effects added to an original source image H_c can be represented as follows:

$$\hat{H}_c(x, y) = H_c(x, y) + S_c(x, y) + G_c(x, y) \tag{1}$$

Where c Є{R, G, B} indicates each RGB colour space channel, x and y are the pixel coordinates. The darkest area of the shadow region is Umbra, while the wide outer boundary with a nonlinear intensity changes between the umbra and lit area of the image is Penumbra. Most of the user-aided approaches to assist boundary detection require careful highlighting of the boundary area. We propose a method that requires only one rough stroke to mark shadow and ghost sample Major contributions of this approach are as follows:

Easy User Input Specification
Previous work requires precise and exact user-inputs defining the shadow and ghost boundaries. This proposed method only requires a segment highlighted by one rough stroke and grows it on an illumination sensitive image to get initial boundaries.

Interval Variable Pixel Intensity Sampling
Previous work considers only interval-fixed sampling around shadow and ghost regions that causes anomalies near uneven shadow boundaries. To solve this, we proposed an interval-variable pixel intensity sampling according to boundary curvature.

Local Group Optimization for Selected Samples
We propose a local group optimization that balances curve fitness value and local group similarities. Unlike previous work, this approach will filter degraded samples that are replaced with their closest pixel values according to a log-normal probability distribution. This will reduces shadow and ghost removal anomalies.

Gradual Colour Transfer
Post-processing effects will lead to inconsistent shadow and ghost removal compared with the lit areas both in tone and as well as in contrast. We make use of statistics in thin shadow boundaries and the shadow scale field to correct these issues.

2 Related Work

Shadows will come into picture when an object covers the light source, are an ever-present characteristic of our visual experience. If we succeed in detecting ghosts and shadows, then we can easily locate object's shape, and decide where objects contact the ground. These Detected shadows and ghosts also contribute information about illumination constraints and scene geometry.

[3]The main intent of this paper is to build multiple human object tracking based on motion assessment and detection, background subtraction, shadow and ghost removal and occlusion detection. This approach uses morphological operations to identify and remove ghosts and shadows in frames. This proposed strategy can potentially operate even in the presence of occlusions in video streams by detaching them.

Advantages:

- Shadow detection accuracy is enhanced by putting spatial constraint between sub regions of foreground i.e. between shadow and human .
- This approach can effectively remove shadows and ghosts in the presence of occlusions also.

Disdvantages:

- This approach cannot preserve the texture contrast.
- This approach fails to perform dynamic background updation while creating reference background image.

[4]This paper is aimed at detection and removal of shadow in a single image of natural scenes. This approach makes use of region based strategy. Besides taking into account the discrete regions individually, this proposal estimates respective illumination data between segmented regions from their appearances and after that performs pair wise classification based on the collected illumination data. It uses Classification results to build graph of segments and later graph-cut method is employed for discriminating the regions shadow and non-shadow. Finally image matting technique is used to purify the detection results .

Advantages:

- This method can effectively identify and abolish shadows and ghosts from a single still image of natural scenes.
- Every individual pixel's illumination conditions are better recovered by soft matting particularly for those which are at shadow areas boundary.

Disdvantages:

- Shading dissimilarities cannot be discriminated because of cast shadows and surface orientations.
- When there are multiple light sources this algorithm may not work properly.

[5] Shadow and ghost extraction from a single compound natural scene was addressed in this paper. No other streamlined assumption is used other than the Lambertian assumption on camera and on the light source. As it can convert the user supplied rough hints to the potential prior and likelihood functions for Bayesian optimization, this method gains the popularity. Reasonable estimation of the shadowless image is needed by the likelihood function, which can be obtained by solving respective Poisson equation.

Advantages:

- Soft and hard shadows can be removed effectively by preserving the texture under extracted regions.
- It can effectively transform user supplied marks into the productive likelihood and prior functions to the Bayesian optimization.

Disdvantages:

- Shading and shadow effects cannot be distinguished is still remains as a limitation in this single image based approach..

[6]This approach for editing, and rendering shadows and ghost edges in a synthetic image or photograph allows users to isolate image component with the shadow and allows users to make some alterations to its sharpness, position and intensity. For modification of shadows in images tools were developed in this paper. Usually shadows will be distinguished by their soft boundaries and varying sharpness details along the edges.

Advantages:

- This technique can remove the shadows without affecting the underlying image texture.

Disdvantages:

- This technique cannot handle the smooth shadow edges.
- Some shadow edges will not be accurately addressed by this approach.

[7] Only with the very less user support this approach uses Constant illumination distance measure to spot lit and shadowed areas on the same surface of the scene. Affine shadow generation model's parameters can be calculated by these areas. In the end reconstruction process which is of type pyramid-based approach is used to provide shadow-free image with texture preserving and no noise inclusion. At the end image inpainting is applied along the thin boarder to assure smooth evolution between original and recuperated regions.

Advantages:

- Texture and color information at the shadow regions can be well recovered with this approach.
- By reconstructing the affine shadow model's parameters, Shadows with varying intensity can be better handled.

Disdvantages:

- Producing shadow-free images with high quality is still not guaranteed in this approach.
- Even after the shadow is removed some shadow residue is still present in the recovered image.

3 Proposed Method

Given an input image and a user specified umbra segment, we detect the initial shadow and ghost boundaries by expanding the given umbra segment on an illumination image using an active contour. To keep boundary details, we sample pixel intensities along the sampling lines perpendicular to the shadow boundary at variable intervals. We perform a local group optimization task to estimate the illumination change which refines shadow boundary detection and provides an initial scale field. According to an adaptive sample quality threshold, sampling lines with bad samples are replaced by their nearest neighbors and a later local group optimization is applied to them. Finally, this approach relights the shadow area using our scale field and correct post-processing artefacts using gradual colour transfer. Our Proposed method has the following 3 steps as shown in fig. 1:

1.Initial Shadow/Ghost Boundary Detection.

2.Scale Field Estimation.

3.Gradual Colour Transfer.

3.1 Initial Shadow/Ghost Boundary Detection

Determining the initial shadow or ghost boundary is the first step of penumbra detection in most of the previous methods[8,9,10]. we fuse four normalised candidate illumination-sensitive channels from different colour spaces into an illumination image. We measure the confidence values of each candidate channel by using an exponential incentive function φ representing the textureness of each of their umbra sample segments:

$$\varphi(x) = x^{-\lambda} \left(\lambda > 0\right) \quad (2)$$

where x is the pixel intensity, λ(default value 5) specifies the steepness of the incentive function. Lower textureness is preferred as it means higher intensity uniformity of umbra segment. The fused image F is computed as a weighted sum of each normalised candidate channel c_l as follows:

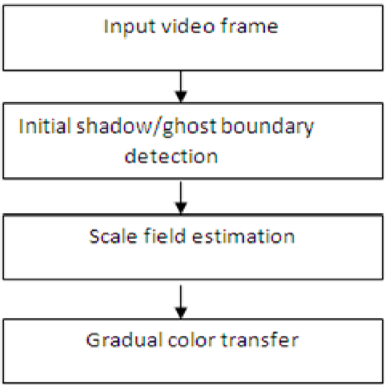

Fig. 1. -Flow diagram of the proposed method

$$\mathrm{F} = \left(\sum_{l=1}^{4} c_l \varphi(\sigma_l) \Big/ \left(\sum_{l=1}^{4} c_l \varphi(\sigma_l) \right) \right) \quad (3)$$

Where l is the channel index, σ_l is the standard derivation of the umbra sample intensities of C_l. To avoid texture noise, we apply a bilateral filter [11] to F first. We grow a sparse-field active contour [12] on the fused image to detect the initial shadow boundary.

3.2 Scale Field Estimation

Shadow and ghost affects are represented by varying (or different scale) intensity values. Using a scale field better represents the penumbra and umbra variations, and is used to relight the shadow/ghost area using Eq. 1.we first sample the log domain pixel intensity along the sampling lines perpendicular to the shadow boundary. We adopt a local group spline fitting optimization through the measured sampling line pixel intensities to estimate sparse scales from the initial intensity samples. We replace bad intensity samples with their nearest alternatives and re-optimize for them.

1. Interval-Variable Pixel Intensity Sampling

According to Eq. 1, the logarithms of the original image are supplied for sampling. We sample pixel intensities along the lines perpendicular to the initial shadow/ghost boundary. Uneven boundaries can result in non-smooth vector normal estimations along the shadow boundary. To overcome this, we apply cubic spline smoothing to the initial boundary points before we compute their normals and curvatures. Under-sampling along the boundary neglects sharp details and causes artefacts, while oversampling incurs penumbra removal noise due to texture. More sparse pixel scales are computed for curvy boundary parts for precise in-painting. To avoid texture artefacts, we apply a bilateral filter to the input image before sampling. Our method adjusts the sampling interval according to the curvature of the smoothed boundary.

2. Illumination Variance Estimation

Having obtained sparse intensity samples at different positions along the boundary, our goal is to find illumination scaling values inside the umbra, penumbra and lit area. We model the illumination scale change S_i for each i^{th} intensity sample of each RGB channel as follows:

$$S_i(x) = \begin{cases} K & x < x_1 \\ f(x) & x_1 < x \leq x_2 \\ 0 & x > x_2 \end{cases} \tag{4}$$

Where x is a pixel location within the sampling line, x1and x2 determine the start and end of the penumbra area respectively, and K is a negative scale constant for sample points within the umbra area (x < x1).

3. Gradual Colour Transfer

Image acquisition devices usually apply the concept of post processing, e.g. Gamma correction. Lossy compressions, e.g. JPEG, are also common in images such that compression artefacts (e.g. affecting contrast) in the shadow area become noticeable when removal is applied. To resolve this, we extend the colour transfer with scale field *Sm*. This approach will compute the normalized scale increase hi of the i^{th} sampling line according to Eq. 5 as follows:

$$h_i(x) = (exp(f_i(x)) - exp(K_i))/(1 - exp(K_i)) \tag{5}$$

Here x is the pixel's location of a sampling line, K_i and f_i are respectively the lit constant K and the cubic function piece of the i^{th} sampling line.

Algorithm UASremoval

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Input:

V: Video

F(1..n) :Frames

U_i: User Input

K(1..f): key frames

S_d: Shadow detection

Output:

Shadow/ghost removed image, S_r.

Method:

```
for input video V
        Convert V into F(1..n)
        For all F1 to Fn
        Compute Shadow detection;
    endfor
 endfor
 for all F1 to Fn do
    select K(1..f)∈ F(1..n)
        for i=1 to f do
        specify Ui on K(1..f) to get Sd and Sr on K(1..f);
        end for
 end for
}
```

This shadow removal algorithm takes video V as input and it converts it into frames F(1..n).This algorithm identifies shadows in all frames F(1..n).Among all frames some of the frames will be considered as key frames k(1..f). For each key frame the user specifies rough sketch U_i on the shadow area .This rough user input will extend up to all shadow region. This algorithm will remove the shadow region from the key frame.

4 Conclusion and Future Work

We have presented a user-friendly texture-preserving shadow and ghost removal method that overcomes some common limitations from the past work. Specifically, our approach retains shadowed texture and performs well on highly-uneven shadow boundaries, non-uniform ghost illumination, and non-white lighting. Our main technical contributions include: (1) highly user-friendly input (2) interval-variable pixel intensity sampling (3) local group optimization and (4) gradual colour transfer. In future work, this approach will focus on more complex cases, such as highly broken shadows, shadowed surfaces with very strong shadow-like textures, and complex reflections in transparent scenes.

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