Shadow detection using multi-features in SVM classifier

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Abstract. Shadows may cause many problems in computer vision, such as object recognition, image segmentation and video surveillance. In this paper, we present a new method to detect cast shadow in a single outdoor image. We build up an illumination model to explain the process of shadow formed, and through this model we introduce some useful features. The regions for extract features are acquired through canny edge detector, after a series of morphological operations. Then we use SVM classifier with a multi-kernel model to train these features for shadow region classification. Our results show that edges of shadow images can be detected effectively with our methods.

Introduction

Shadows are physical phenomena which commonly found in natural scenes \cite{1}. It often causes many problems in computer vision, such as image segmentation, edge detection, object recognition, and tracking \cite{2}. In recent years, some researchers were attracted to this topic, and have also proposed approaches that specifically focus on the detection of shadow \cite{3-5}. Based on shadow detection, some shadow removal methods also can be used to removal shadows. Detecting and removing significantly improve tasks in computer vision and image processing. So shadow detection will attract more and more attentions.

Single image shadow detection is still a challenging and open task. Early methods mainly depend on learning approaches and physical approaches \cite{1-4}. The learning methods usually exact some shadow features and apply the classifier to detect shadow. Zhu et al. \cite{10} divided shadow feature into shadow-variant and shadow-invariant cues, and use boosting decision tree to detect monochromatic natural images. Lalonde et al. \cite{3} trained an Adaboost decision tree based on color and texture features, and combine it with scene layout cues. Guo et al. \cite{4} trained the SVM classifier with the RBF kernel to detect shadows. Some methods depend on physical model also perform well \cite{5-9}. Jung et al. \cite{9} discovered a new model derived from a so-called Retinex principle, and well suited for single image shadow detection. Tian et al. \cite{6} proposed tri-color attenuation model to describe the attenuation relationship between shadow and non-shadow background, and use this model to detect shadow.

Learning methods are good robust for detection, while physical methods usually cost little time to detect. So we will combine the two methods, analyze the features in physical method and use SVM classifier to train these features. We first collect a large amount of shadow images, and label the shadow edge manually for training. In each image, we use canny detector to acquire boundaries. Based on the training results of SVM, shadow edges can be distinguished.
Shadow formation

There are mainly two types of light sources in outdoor scenes: sunlight and skylight. Shadows will generate when sunlight is partially or completely obscured, and only illuminated by skylight. As shown in fig.1. Cast shadow also can be further divided into umbra and penumbra region. We denote \[ \mathbf{F} = [f_R, f_G, f_B] \] as a vector of a pixel in a color image. \[ \mathbf{F} \] is a mean values vector of a region in this image. \[ [F_{SR}, F_{SG}, F_{SB}] \] is the value vector of shadow region, and \[ [F_{NR}, F_{NG}, F_{NB}] \] is the value vector of non-shadow region.

![Shadow formation diagram](image)

Fig.1. Left: Shadow formation processing, right: shadow ground.

Based on the principles of shadow forming, we describe four physical shadow properties as follows:

**Intensity difference**: Since skylight is a part of sunlight, pixel intensity in shadow must be lower than that in non-shadow region. In more detail, the intensity changes between shadow and non-shadow region usually perform great due to each edge, whereas material changes rarely have this phenomenon. So the Intensity Difference can be an efficient feature to detect shadow.

**Texture similarity**: Across shadow boundaries, the textural properties of surfaces are changed little. It’s the reason that we can still discern the originally appearance of the object. We extract the histograms of texture of an image region using the method introduced in [3]. We also measure the similarity using Euclid distance of the difference between histograms of texture values for neighboring regions.

**Color ratios**: The two sources have different properties, sunlight seems to be red and skylight is blue. Using this natural phenomenon, we can calculate the RGB ratio over a boundary. The mean value of shadow regions is \[ [F_{SR}, F_{SG}, F_{SB}] \], and that of non-shadow regions is \[ [F_{NR}, F_{NG}, F_{NB}] \]. Thus the RGB ratio from the shadow side (the darker side) can be calculate by:

\[
\begin{bmatrix}
\frac{F_{SR}}{F_{SR} + F_{NR}} \\
\frac{F_{SG}}{F_{SG} + F_{NG}} \\
\frac{F_{SB}}{F_{SB} + F_{NB}}
\end{bmatrix}
\]

**Three channels attenuation**: Similar to color ratios, the attenuation relationship between shadow and non-shadow region in RGB channels also seem to be different. Tian et al. [6][11] also gave the derivation using the TAM model, and limited the attenuation to certain range. We adopt the vector \[ \Delta \mathbf{F} = \Delta \mathbf{R}, \Delta \mathbf{G}, \Delta \mathbf{B} \] as the cue to distinguish shadows. Where,

\[
\begin{align*}
\Delta R & = F_{NR} - F_{SR} \\
\Delta G & = F_{NG} - F_{SG} \\
\Delta B & = F_{NB} - F_{SB}
\end{align*}
\]

Date sets

We have collected a database consisting of 500 images. In this database, 245 of these images were collected by Zhu et al. [10]. Their dataset include 74 aerial images from the Overhead Imagery Research Dataset and 54 images from LabelMe dataset, the others were catch in outdoor
environments. We download 126 images from Google Image, and also capture 129 images in surrounding environment. From the dataset, we randomly selected 200 images as training data, the other 300 images are used as test data.

**Shadow detection**

In our experiments, four physical features are combined to address the problem of shadow detection. The advantage of adding physical features into shadow detection can significantly reduce detection time. The structure of our approach is showed in fig.2.

Fig. 2. A flow chart of our proposed shadow detection algorithm.

We employ the canny detector to obtain image boundaries, using the threshold subtraction with two adjacent thresholds from 0.9 to 0.2. Based on these boundaries, we apply a binary dilation operation on both sides. Then we obtain the shadow region (or darker region) and non-shadow region (lighter region) after erosion the origin edge. The regions are used to extract features that we introduce in last section. Multi kernel SVM is employed to train these features, and successfully to distinguish shadow and non-shadow regions.

**Experiment results**

We evaluate our shadow detection algorithm on the dataset. Four of qualitative results are showed in fig.3. The first row are the origin images, the second row are the ground truth, the third row are our detection results.

Fig.3. Some qualitative results in our experiments

For quantitative results, the edge-grade Precision-Recall and F-measure of these images are shown: **precision rate: 63.43% recall rate: 71.43%, F-measure: 0.67**; Recall is true shadow
edges in detected shadow edges, and Precision is the shadow detection rate in real shadow edges, and

\[
F\text{-measure} = \frac{2}{1/\text{precision} + 1/\text{recall}}
\]  

(3)

**Conclusion**

In this paper, we detect single shadow image using multi-features in SVM classifier. First, we obtain shadow boundaries using the canny edge detector. Secondly, regions are selected to extract features through morphology operator. Then we bring these features to SVM with kernel, and we got an effective classifier to distinguish shadow. Finally, we use our proposed method to detect shadows and perform well in our experiment results.

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