A Color Intensity Variation based Approach for Background Subtraction and Shadow Detection

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Abstract

Computational speed plays key role in background subtraction and shadow detection, because those are only preprocessing steps of a moving object segmentation, tracking and activity recognition. A color intensity variation based approach fastly detect a moving object and extract shadow in a image sequences. The moving object is subtracted from background using meanmax, meanmin thresholds and shadow is detected by decrease limit and correspondence thresholds. The proposed approach relies on the ability to represent shadow cast impact by offline experiment dataset on sub grouped RGB color space.

1 Introduction

Detection and tracking of moving objects is at the core of many applications dealing with image sequences. Shadow detection approaches can be classified into two groups: model-based, and property-based approaches. Model-based approaches rely on models representing the a priori knowledge of the geometry of the scene, the objects, and the illumination.. Model-based techniques are designed for specific applications, such as aerial image understanding [1-2] and video surveillance [3-4]. Property-based approaches identify shadows by using features such as geometry, brightness or color of shadows. Most of the current property-based approaches are based on an assumption that the shadow pixels have the same chrominance as the background but are of lower luminance. For instance, Horprasert *et al.* [5], classify a pixel into one of the four categories depending on the distortion of the luminance and the amount of the chrominance of the difference. Stauder [6] provided a similar approach by verifying the above criteria by integrating a color model similar to Phong. Mikic *et al.* [7] classified pixels on the basis of a statistical method. Fatih *et al.* [8] model shadows using multivariate Gaussians. This method does not need a color space transformation. Hanzi *et al.*[9] proposed SACON: which gathers background samples and computes sample consensus to estimate a statistical model at each pixel. Nurul *et al.* [10] used in Gaussian Mixture Model in Improved HLS color space. A comparative study of many cast shadow segmentation algorithms can also be found [11].

1.1 The difference between previous approaches and proposed one

Model-based approaches relied on matching sets of geometric features such as edges, lines or corners to 3D object models. Model-based schemes generally handle simple objects and are only applicable to the specific application they are designed for. The above-mentioned limitations are overcome by using spectral and geometric features of shadows in property-based approaches. In other hand, current above mentioned property-based approaches used complex techniques which are relied on statistic or color models such as chromaticity and brightness distortion, Gaussian, Mixture of Gaussian, HSV, Improved HLS etc…. Although such techniques might be generally computationally expensive, and it could be play a negative role in an overall application speed. Reason of complexity is those techniques are comprises the background and shadow pixels modeling.

We proposed a generally property-based approach but also extended it by with a priori knowledge from offline experiments. The novelty is in the separate modeling of background and shadow pixels. First, we exploit the shadow impacts on different colored pixels from background in offline experiments. Then using these experiment data, we have been building shadow impact dataset, which defines:

- exactly how much will decrease certain color's RGB intensities
- and how will correspondingly change the certain color's RGB intensities

Revealing these two fundamental properties of shadow impact for all colors is core achievement of our research.
The paper is organized as follows. The proposed approach is described detail in Sec. 2. Section 3 shows experimental results and finally Sec. 4 summarizes the paper.

2 A Color Intensity Variation based Approach

The color intensity variation approach is based on property of cast shadow impaction on pixel's color intensity. We apply the proposed approach in a background subtraction and shadow detection processes. The approach consists from two stages. See Figure 1.

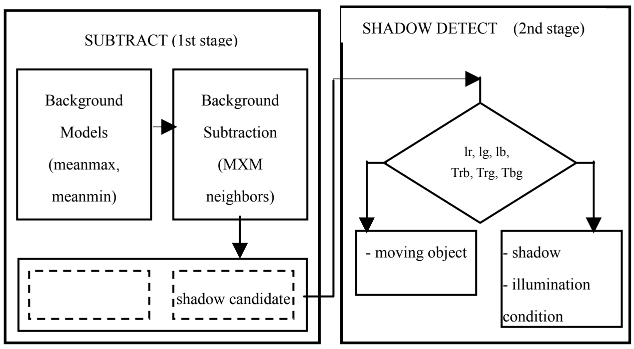

Fig. 1. Stages 1 and 2 of the proposed method

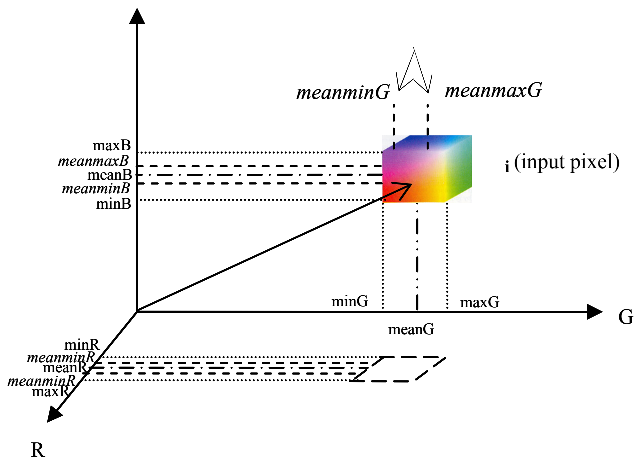

Fig. 2. The Background model – separate evaluation of each pixel's RGB color intensities

The first stage of the proposed algorithm is subtraction of moving object with shadow in each frame of the video sequence. This stage exploits the property that moving object's intensities different than background intensities. In second stage, detects shadows from previous moving object by reduced color's intensities. In both stages, changes in the intensity values of the three color channels R; G; B analyzed.

2.1 Background Subtraction

Bmin

In the subtraction stage, variation of intensity values is checked by comparing the current frame and a reference frame. The reference frame represents the background of the scene, an image which does not contain dynamic objects nor shadows due to moving objects. The image difference D(x, y), computed as D(x, y) = I(x_r, y_r)-I(x, y) at each pixel (x, y) position belonging to the detected objects, is considered. The image I(x, y) = (R(x, y),G(x, y),B(x, y)) and (x_r, y_r) belongs to the reference image and corresponds to the pixel (x; y) under analysis. In a noise free case, the condition D(x, y) <> 0 would suffice to state that the pixel (x, y) belongs to a candidate object. In real situation, the noise introduced by the acquisition process alters the above test, so that it becomes D(x, y) > b, where threshold from MXM neighborhood pixel's value. In our case M is 5. In the background subtraction process, first we calculate mean, maximum, minimum of intensity value Red, Green, Blue color channels at each pixel over the N frames, correspondingly $min_{R,G,B}$, $max_{R,G,B}$, $mean_{R,G,B}$. See Figure 2. Here, minG, maxG, are is minimum and maximum of Green color channel's intensity. We test on N=200 image frames. Then we define $meanmax_{R,B,G,}$, $meanmin_{R,G,B}$ *thresholds,* as corresponding mean of all values that greater or smaller than mean of color's intensity and $TempRef_{R,G,B}$ (temporary reference) as the mean of the each pixel. Finally we get moving foreground object's shape, using these thresholds in MXM neighborhood pixels.

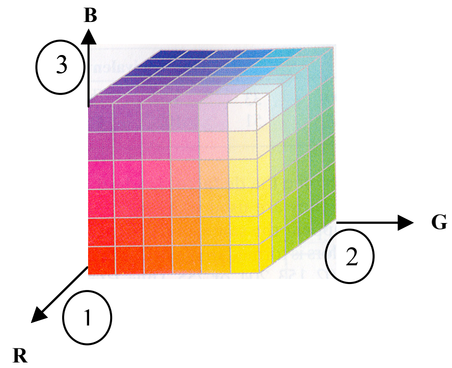

Fig. 3. 216 sub grouped RGB color space. Numerating order is following first Red then Green, Blue values and one group size is around 42X42X42.

2.3 Automatic shadow referencing method

Shadow variously impacts into the pixel's color intensity. We have been experimenting shadow test on 216 sub grouped RGB color space. See Figure 3. We developed automatic shadow referencing method for RGB color space. The method collects data from test background with cast shadow in offline experiment and builds shadow impact dataset with decrease limit thresholds and correspondence thresholds. In an offline experiments, we analyze 200 image frames. First 50 frames are analyzed for reference color of dataset $DsRef_{R,G,B}$. And these reference colors are automatically grouped to the RGB sub color spaces. Then next 150 frames are analyzed for reveal shadow impacts. The analyses of revealing shadow impact consists from two steps. The first step is for definition of the decrease limits thresholds of color channels: Dl_R, Dl_G, Dl_B. Decrease limit is lowest peak of color intensity and used for checking whether the current color intensity is in range or not. In the next step, correspondence thresholds are calculates by differentiating between RGB color intensities: Ct_{RG}, Ct_{RB}, Ct_{GB} (difference value between red and green, red and blue, green and blue respectively). Then, shadow impact dataset is modeled by dataset reference - $DsRef_{R,G,B,}$, decrease limit Dl_R, Dl_G, $Dl_{B,}$ and correspondence Ct_{RG}, Ct_{RB}, Ct_{GB} thresholds.

2.4 Shadow detection

In the shadow detection stage, from the subtracted as object pixel's the condition D(x, y) > 0 would suffice to state that the pixel (x, y) belongs to a candidate shadow. And this current pixel is modeled by $meanmax_{R,B,G}(x,y)$, $meanmin_{R,G,B}(x,y)$ *thresholds* and $TempRef_{R,G,B}$ *(x,y)*.

Our shadow detection algorithm consists from next steps:

1. References matching between $DsRef_{R,G,B}$ and $TempRef_{R,G,B}$ *(x,y)*.
2. Check intensity decrease limits by Dl_R, Dl_G, $Dl_{B.}$ We check whether is decreased intensity values in range of decrease limits. (See Figure 4.)
3. Check color intensity correspondences by thresholds Ct_{RG}, Ct_{RB}, $Ct_{GB.}$

We check relationship between color channels according to correspondence thresholds.

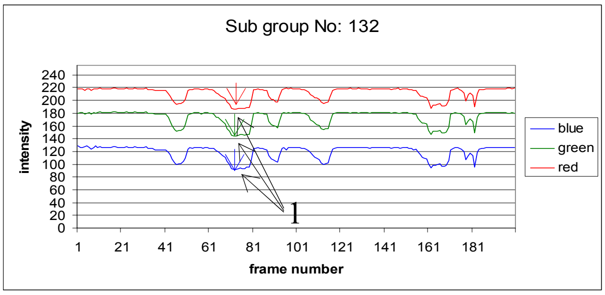

Fig. 4. Decrease limit thresholds

3. Experimental part

We have been manually or artificially creating the shadow on the background's specific colors.

Figure 6 shows examples of current experiments. In the first example, shadow impact initial background pixel's (which is in the sub group No: 132) mean intensities of R=220, G=180, B=132. In this experiment, all three channel's intensities almost same impacted. But in second example, only two color channel's intensities are impacted and third blue color channel's intensity causing from its low value, almost not influenced. It shows one of properties of shadow impact. In other experiments, if there are all three intensities were lower values, even no influence of changes in those intensities. For example, previously mentioned experiments, we first selected our laboratory's wall, then on specific location we manually cast a shadow after background modeling process. Following this method, we also experimented on red like paper viewed by camera and received data which shows how cast shadow impacted. In this case, the intensities were now robust.

The manually or artificially shadow creating method from one side time consuming, but in other hand it gives very robust data of shadow impacting, from weak to deep. So, in certain illumination condition, we can previously assume that how may change the specific background's color when casting a shadow.

Currently, we have been experimenting in indoor environment. Figure 5 shows background subtraction and shadow detection algorithm's result. Here, using only $meanmax_{R,B,G,}(x,y)$ $meanmin_{R,G,B}(x,y)$ *thresholds* background subtraction processed very fast and in accepted accuracy.

4 Summary

The proposed background subtraction and shadow detection algorithm is based on two stages. In the first stage, the algorithm processing background subtraction of moving object with shadows in each frame of a sequence, using the $meanmax_{R,B,G,}$, $meanmin_{R,G,B,}$ thresholds. This thresholding method fastly subtracts all differences between reference image and current image in an acceptible accuracy. In the second stage, the algorithm detects shadow pixels by its reduced color intensity values. The novelty of our approach is in the separate modeling

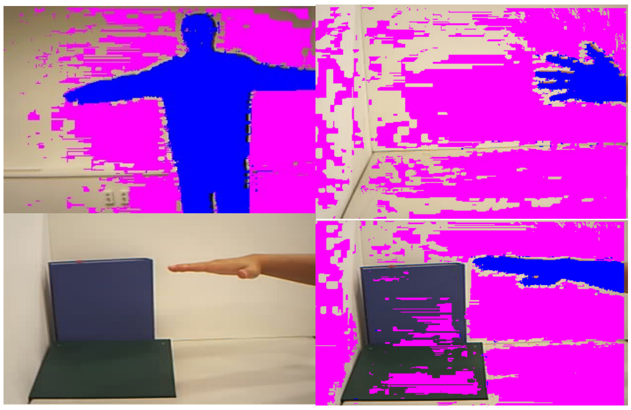

Fig. 5. Background subtraction and shadow detection algorithm

of background and shadow pixels. Currently we have been experimenting in indoor environment with similar to D65 daylight illumination condition. Future work includes the completion of shadow impact dataset and extension of experimenting environment's illumination condition into four different standard types.

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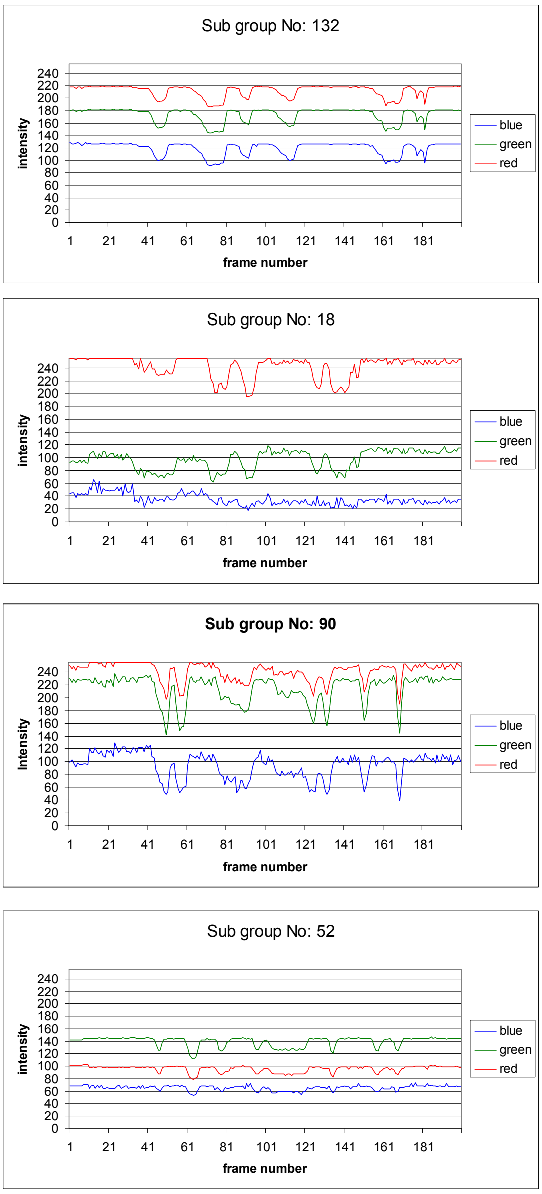

Fig. 6. Cast shadow impacts on different colored background pixels