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Method of Updating Shadow Model for Shadow Detection based on Nonparametric Bayesian Estimation

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Abstract

Detecting shadows is needed for object detection methods because shadows often have a harmful effect on the result. Shadow detection methods based on shadow models are proposed. The shadow model should be updated to detect shadows which are not included in the learning data. In this paper, a new method for updating the shadow model for shadow detection is proposed. The proposed method models shadows by the Gaussian mixture distribution. The parameters of the distributions are estimated by the Dirichlet Process EM (DPEM) algorithm, which is a nonparametric Bayesian scheme. Shadows are detected by the probability density calculated with the shadow model. The detected result is improved by using the color segmentation method. The data which are not included in the learning data for the current shadow model are obtained by comparing the results. The DPEM algorithm is applied to the frequency distribution of the data to obtain initial parameters. After that, it is applied to the frequency distribution of the data which are obtained as shadow data in past frames and the new shadow model is constructed. Results are demonstrated by experiments using real video sequences.

1 Introduction

In many fields of computer vision, a detection method of moving objects is used as a preprocessing. Many methods for object detection have a problem that shadows are detected as moving objects. Shadows often have a harmful effect on the result. Methods for object detection require a method for detecting and removing shadows.

Methods which convert color space to remove shadows are proposed[1][2]. It is difficult for them to remove all shadows stably in any conditions. Shadow detection methods using shadow models are proposed [3][4]. They model shadows by the Gaussian mixture distribution models and the number of distributions should be determined in advance. It is difficult to know the proper number of distributions. The shadow detection method based on nonparametric Bayesian model is proposed[5]. The method uses Dirichlet process mixture (DPM) model, which is a typical nonparametric Bayesian model, for the prior distribution of the Gaussian mixture distribution. This method cannot detect shadows which are not included in the learning data of the shadow model. Shadow models for the shadow detection methods should be updated to keep detecting shadows with high performance in such a case.

This paper proposes a new approach for updating the shadow model. The shadow detection method of the proposed method is based on the method[5]. The detected result is improved by using the color segmentation method. The improved result includes shadows which are not included in the learning data. They are used for updating the shadow model. The Dirichlet Process EM (DPEM) algorithm[6] is applied to the frequency distribution of the data to obtain initial parameters. After that, it is applied to the frequency distribution of the data which are obtained as shadow data in past frames and the new shadow model is constructed. Results are demonstrated by the experiments using the real videos.

2 Shadow Model

The proposed method models shadows after converting RGB color space into YUV color space. The method uses a background image. The differences of U and V components of each pixel in shadow regions between the background image and a target image become small but the difference of Y component becomes large. On the other hand, the differences of all components in regions of moving objects become large. The proposed method uses the differences of YUV components as the observed data.

The Gaussian mixture model is used for the shadow model. The model is constructed by the data in shadow regions. After the frequency distribution of the data is obtained, the probability of occurrence for the frequency distribution is approximated by the Gaussian mixture distribution. It is used as the shadow model.

The parameters of the distribution are estimated by a nonparametric Bayesian scheme. The proposed method uses the DPM model, which is a typical nonparametric Bayesian model, as the prior distribution of the Gaussian mixture model. The DPM model is a very flexible model because it can define a probability model with countably infinite distributions. In fact, it is difficult to treat the infinite distributions. The distributions are truncated at a sufficiently large number of distributions. The effect of truncation to the approximation is very small because many distributions hardly contribute to the mixture distribution in many cases.

The proposed method uses the DPEM algorithm to estimate the parameters of the distribution. It is based on the EM algorithm and can be implemented easily. The DPEM algorithm uses Stick Breaking Process (SBP)[7], which is an intuitive approach for the Dirichlet process, as the prior probability distribution for the mixture ratio of the distribution. The algorithm can calculate not only the parameters of the mixture distribution but also the mixture ratios. When they are estimated, the DPEM algorithm uses a sufficiently large number of distributions. After estimating the mixture ratios, the number of the distribution for the shadow model is determined according to the mixture ratios. The mixture model where the distributions with a small number of mixture ratios are removed is treated as the shadow model.

3 Shadow Detection

After constructing the shadow model, shadows are detected by using the model. The detection process is as follows: At first, the probability that a pixel exists in the shadow region is calculated. Next, the shadow regions and the object regions are separated through the threshold processing. The shadow detection process is applied to pixels extracted by the background subtraction. The detection process and the process for refining the result are explained in the following.

Let the number of the distribution be K. The probability that a pixel $\boldsymbol{x}$ belongs to the shadow region is calculated by Eq. (1).

$$p(\boldsymbol{s}(\boldsymbol{x})|\boldsymbol{\alpha},\boldsymbol{\theta}) = \sum_{k=1}^{K} \alpha_k \mathcal{N}(\boldsymbol{s}(\boldsymbol{x});\boldsymbol{\theta}_k) \tag{1}$$

$$\boldsymbol{\alpha} = \{\alpha_1, \cdots, \alpha_K\}, \quad \boldsymbol{\theta} = \{\boldsymbol{\theta}_1, \cdots, \boldsymbol{\theta}_K\}$$

where $\boldsymbol{s}(\boldsymbol{x})$ means the data at $\boldsymbol{x}$, $\mathcal{N}(\cdot\ ;\boldsymbol{\theta}_k)$ means the k-th Gaussian distribution, α_k means the mixture ratio for the k-th distribution and $\boldsymbol{\theta}_k$ means the parameters of the k-th distribution. α_k and $\boldsymbol{\theta}_k$ are estimated by the DPEM algorithm.

$p(\boldsymbol{s}(\boldsymbol{x})|\boldsymbol{\alpha},\boldsymbol{\theta})$ becomes large when the pixel exists in a shadow region. $\boldsymbol{x}$ is regarded as the pixel in the shadow region when $p(\boldsymbol{s}(\boldsymbol{x})|\alpha,\boldsymbol{\theta})$ is larger than a threshold. Otherwise, $\boldsymbol{x}$ is regarded as the pixel in the object region.

After the threshold processing, the process for refining the result is applied. The refinement process is shown in the following. First, the observed image is segmented by color. The Mean-Shift segmentation[8] is used for color segmentation. Next, it is judged whether each region belongs to the shadow region or not. A region where more than 60% pixels in the region are recognized as pixels in the shadow region by the above process is recognized as the shadow region. It is determined that all pixels in the regions exist in the shadow region. Otherwise, it is regarded as the object region and all pixels in the region are regarded as pixels in the object region.

4 Updating Shadow Model

The proposed method obtains the data manually in the shadow regions to learn the initial shadow model. The shadow model is updated in order to detect shadows which are not included in the learning data. The shadow regions detected through the previous process are used for updating the model. The process for updating the model is as follows:

STEP1 Updating the learning data
STEP2 Obtaining the initial values for DPEM algorithm
STEP3 Updating the shadow model by DPEM algorithm

STEP1 and **STEP2** are described in the following.

4.1 Updating Learning Data

The proposed method stores the data of pixels which were detected as pixels in shadow regions at the past frames. When all data of the past frames are stored, a great deal of time is required to handle the DPEM algorithm because the number of data becomes enormous. Furthermore, the impact of shadow data which are obtained at the current frame becomes small. The method for obtaining the learning data is described in the following.

First, misjudged pixels in the object region are removed. The proposed method can extract the object region. The data of pixels extracted as those in the object region is used for removing misjudged pixels. Object regions are labeled and following process is applied to each object region. The variance-covariance matrix for the coordinates of the pixels which are regarded as pixels in the object region is calculated and 95% probability ellipse is obtained. The data of the pixels which exist within the ellipse and are regarded as pixels in the shadow region are removed. The obtained data are added to the learning data. At this time, the data of pixels which were regarded as the shadow region at the past frames are overwritten. This process prevents the method from handling the enormous data.

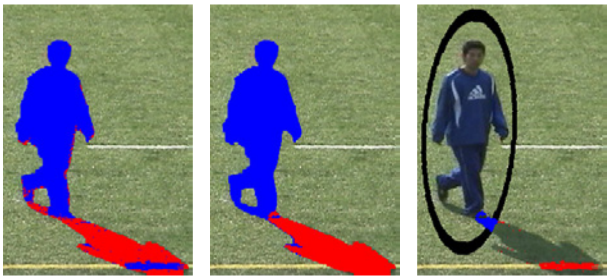
4.2 Obtaining Initial Parameters

Accuracy of the estimated result by the DPEM algorithm depends on initial values of parameters. The following process is applied to give better initial parameters. Parameters which should be given are mean vector and variance-covariance matrix for each Gaussian distribution. A sufficiently large number of distributions for truncation is also required.

The number of distributions is determined by the following process.

STEP1 Obtaining data which are not included in the learning data
STEP2 Applying the DPEM algorithm to the data obtained by **STEP1**

At **STEP1**, the data which are not included in the learning data are obtained. The pixels of which the judgments are corrected to the shadow region from the object region are obtained. Figure 1 shows the



(a) (b) (c)

Figure 1. Process for Detecting Data not Included in Learning Data: (a) Result by Threshold Processing, (b) Result by Segmentation Process, and (c) Data used at **STEP2**

process for **STEP1**. Blue pixel in the figure means it is regarded as a pixel in the object region and red one means it is regarded as a pixel in the shadow region. The blue pixels in Figure 1-(c) are used for the learning data at **STEP2**.

At **STEP2**, the DPEM algorithm is applied to the data obtained through **STEP1**. The sufficiently large number of distributions for truncation for this process is set to 20. The initial mean vector for each distribution is set to a datum obtained randomly from the data. The initial variance-covariance matrix is set to the variance-covariance matrix which is calculated from the data. After the DPEM algorithm is applied, the number of distributions for the data is determined according to the mixture ratios. The truncation number is determined by adding the number of distributions obtained by the above process to the number of distributions for the current shadow model.

The parameters for the current shadow model and those obtained through the above process are given for the initial parameters and the DPEM algorithm is applied to the shadow data. Giving better initial parameters makes the algorithm converge faster and estimate the parameters with high accuracy. The proposed method can estimate parameters better and faster.

5 Experiments

The experiments using the real images were done to confirm the effectiveness of the proposed method. The size of each frame is 720×480 pixels and each pixel has 8bit color value for each RGB component. Three different scenes (Scene1, Scene2 and Scene3) were used in the experiments. The examples of input images used for the experiments are shown in Figure 2.

The results of shadow detection are shown in Figure 3. The blue region in those figures means the object region and the red one means the shadow region. The results show that the proposed method can detect most shadows in all results shown in Figure 3. Some pixels in the shoes region are misjudged as those in the shadow, because the colors of them are similar to those of the shadow.

Two metrics proposed in [9] are introduced to evaluate the results. One is the shadow detection rate η, and the other is the shadow discrimination rate ξ. η and ξ are calculated by Eq. (2).

(1)
(2)
(3)

(a) (b)

Figure 2. Input Images: (1) Scene1, (2) Scene2 and (3) Scene3

Table 1. Shadow Detection Rates ($\boldsymbol{\eta}$) and Shadow Discrimination Rates ($\boldsymbol{\xi}$)

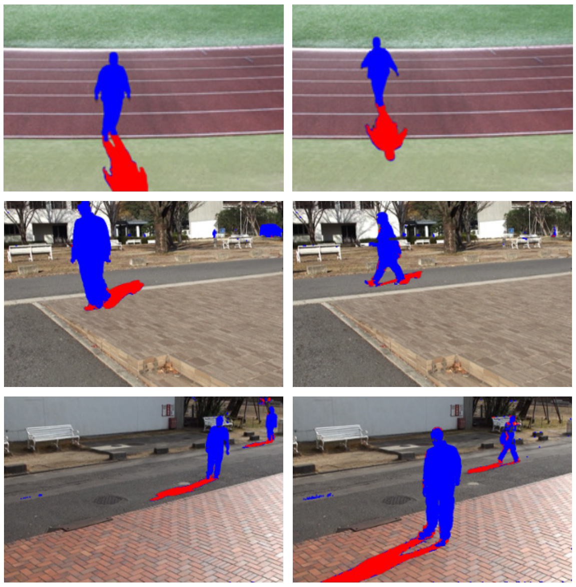
scene	1-(a)	1-(b)	2-(a)	2-(b)	3-(a)	3-(b)
η[%]	96.39	94.37	92.19	89.12	90.21	90.03
ξ[%]	99.42	95.91	95.34	93.11	95.78	96.28

$$\eta = \frac{TP_s}{TP_s + FN_s}, \quad \xi = \frac{\overline{TP}_f}{TP_f + FN_f} \tag{2}$$

where TP means the number of true positives, FN means the number of false negatives, the subscription s means shadow, subscription f means foreground and $\overline{TP}_f$ means the number subtracting the number of points misjudged as shadows on foreground objects from the correct number of points of foreground objects. Table 1 shows η and ξ of each scene for the proposed method. η of all scenes are more than 89 % and ξ of all scenes are more than 93 %. It is shown that the proposed method detects shadows with high performance.

The results of Scene1 by the proposed method without updating the shadow model are shown in Figure 4 to show the effectiveness of updating the model. The results show that the proposed updating method can construct better shadow model and this causes better result. η and ξ for this case are shown in Table 2. ξ for some scenes in Table 2 are better than those in Table 1 but ξ tends to become larger when η becomes smaller. These tables show that the better result of shadow detection can be obtained by updating the shadow model.

The experimental results by the methods [3][5] are shown in Figure 5 to compare them with the proposed method. The method [3] tends to misjudge pixels in dark object regions as those in shadow regions. The shadow model for the method [5] is constructed by the shadow data on the green field. The method [5] cannot detect the shadow on the course because it does not



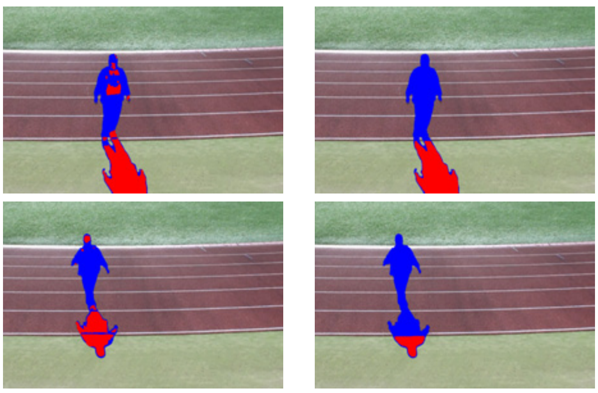
(1) (2) (3)

(a) (b)

Figure 3. Results: (1) Scene1, (2) Scene2 and (3) Scene3

(a) (b)

Figure 4. Results for Scene1 by Method without Updating Shadow Model



(a) (b)

Figure 5. Results for Scene1 by (a) Method [3] and (b) Method [5]

update the shadow model.

6 Conclusion

This paper proposed a new method for updating the shadow model for shadow detection. The proposed method uses the Gaussian mixture model under the Dirichlet process mixture model as the shadow model. The parameters of the model are estimated by the DPEM algorithm. After modeling the shadows

Table 2. $\boldsymbol{\eta}$ and $\boldsymbol{\xi}$ by Method without Updating Shadow Model

scene	1-(a)	1-(b)	2-(a)	2-(b)	3-(a)	3-(b)
η[%]	93.15	34.63	54.72	69.77	79.45	8.14
ξ[%]	99.70	100.00	98.78	99.06	98.61	99.95

by the Gaussian mixture model, the probability that a pixel belongs to the shadow region is calculated and shadow regions are obtained through threshold processing. The result is refined by the color segmentation method. These results are used as the data for updating shadow model. The data which are not included in the learning data for current shadow model are extracted and the DPEM algorithm is applied to the frequency distribution of the data. This causes giving better initial parameters and the number of distributions to the DPEM algorithm. The experimental results show the effectiveness of updating the shadow model. They also show that the proposed method can detect shadows with high performance.

Future work includes determining the parameters for the initial shadow model automatically. Increasing the accuracy of the result by introducing the features which are not based on object's appearance is also needed.

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