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Probabilistic BPRRC: Robust Change Detection against Illumination Changes and Background Movements

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Abstract

This paper presents PrBPRRC (Probabilistic Bipolar Radial Reach Correlation), a change detection method that is robust against illumination changes and background movements. Most of the traditional change detection methods are robust against either illumination changes or background movements; BPRRC is one of the illumination-robust change detection methods. We introduce a probabilistic background texture model into BPRRC and add the robustness against background movements and foreground invasions such as moving cars, walking pedestrians, swaying trees , and falling snow. We show the superiority of our PrBPRRC under the environment with illumination changes and background movements by using public datasets: ATON Highway data, Karlsruhe traffic sequence data, and PETS 2007 data.

1 Introduction

Amid rising concerns about security, surveillance systems have become a focus of attention in recent years. To realize practical surveillance systems, robust change detection for preprocessing is required. Change detection reduces the processing area of time-consuming processes such as object recognition, human detection, and human behavior analysis; therefore, it reduces processing time of the whole system and increases the performance by reducing false positive detection from background region.

Though the environments in which practical surveillance systems operate may include many large disturbances such as illumination changes and background movements, most of the traditional change detection methods are robust against either illumination changes or background movements. For example, Bi-polar Radial Reach Correlation (BPRRC) [1] is robust against illumination changes by using texture model but not robust against background movements because of its rigid texture model.

We propose Probabilistic BPRRC (PrBPRRC), the extension of BPRRC, which preserves BPRRC's robustness against illumination changes and adds the robustness against background movements. PrBPRRC introduces a probabilistic model for background texture and learns a probabilistic background with inputs including background movements and foreground invasions. We show the superiority of our PrBPRRC with ATON Highway data [2], Karlsruhe traffic sequence data [3], and PETS 2007 data [4].

In this paper we make several assumptions to define "change detection": (i) the camera is fixed so that background subtraction which compares input with learned background model can be used for change detection, (ii) change includes foreground objects which deviate from learned background, and (iii) change doesn't include background movements and illumination changes. These assumptions are natural in surveillance system.

The rest of this paper is organized as follows. We briefly review several former change detection methods in Section 2. We then describe the former BPRRC and our proposed PrBPRRC in Section 3. We compare the performance of the methods with public datasets in Section 4 and conclude in Section 5.

2 Related Works

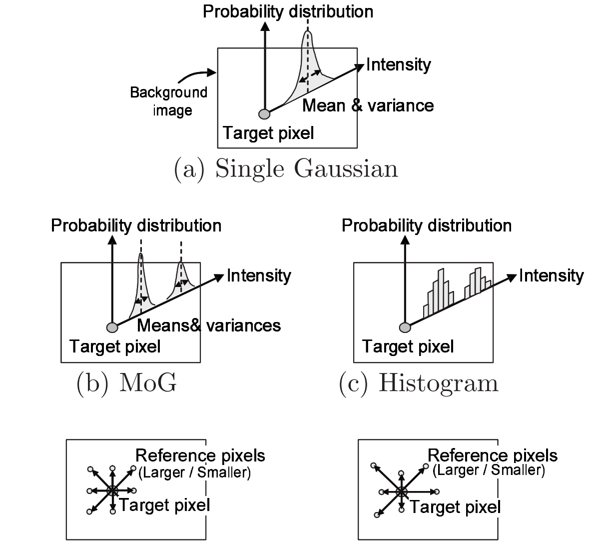
Many background models for change detection have been proposed. One of the simplest background models is the single Gaussian model that models each pixel intensity with a single Gaussian distribution (Fig. 1(a)). The Gaussian distribution can model intensity fluctuation of each pixel caused by sensing devices but the model is too simple to model real environmental changes.

Stauffer et al. proposed Mixture of Gaussian (MoG) [5] that uses multiple Gaussian distributions to model multiple background intensity distributions caused by ripples on the water surface and flickering of the display (Fig. 1(b)). MoG is used in many applications but requires a decision on the number of Gaussian distributions. To avoid this decision, Nakai proposed a non-parametric pixel intensity model with pixel intensity histogram [6] (Fig. 1(c)). Because, in contrast to the Gaussian model, it doesn't assume any parametric models, it can model arbitrary intensity distributions.

Pixel-intensity-based models such as MoG and the histogram model are not robust against illumination changes because illumination changes cause large intensity changes deviating from the past intensity history. For example, background models trained with images in the sun cannot cover inputs in the shade. To increase robustness against illumination changes, some methods introduced texture information. Texture information based on the intensity differences among local pixels is stable against illumination changes because all the local pixels change their intensities by almost the same amount and the intensity differences among them don't change. Satoh et al. proposed Peripheral Increment Sign Correlation (PISC) [7] and Heikkilä et al. proposed Local Binary Pattern (LBP) [8] that encode the intensity differences between target pixel and surrounding reference pixels as 0/1 binary code (Fig.

1(d)). Yokoi proposed Peripheral TErnary Sign Correlation (PTESC) [9] that encodes the intensity differences by $-1/0/1$ ternary codes to increase the robustness against illumination changes.

Though these texture-based methods are robust against illumination changes, they cannot work properly in the region without texture. Plain foreground objects before plain background with different intensity from foreground cannot be detected by these methods because both foreground and background have the same plain texture.



(a) Single Gaussian

(b) MoG (c) Histogram

(d) PISC/LBP/PTESC (e) BPRRC

Figure 1: Schematics of the background model of former change detection methods

3 Probabilistic BPRRC

3.1 BPRRC

Bi-polar Radial Reach Correlation (BPRRC) [1] is one of the texture-based change detection methods and can work properly in the region without texture (Fig. 1(e)). It searches the far reference pixels with enough intensity differences from a target pixel by skipping the plain region so that it can detect plain foreground objects before plain background.

In the training stage, BPRRC searches reference pixels with positive intensity difference above a threshold from a target pixel $Bg(x, y)$ in 8 directions in a background image Bg. Then, it saves the position of the reference pixels as $b_k^+(x, y)\,(k = 0, ..., 7)$. In the same way it searches reference pixels with negative intensity difference and saves the positions as $b_k^-(x, y)$. In the detection stage, in an input image I, it compares intensity differences between target pixel $I(x, y)$ and its 16 reference pixels $I_{b_k^{\pm}}(x, y)$ that correspond to $b_k^{\pm}(x, y)$ in I and detects changes based on the correspondence $B(x, y)$ between background and input:

$$B(x,y) = \frac{1}{16}\{\sum_{k=0}^{7} B_k^+(x,y) + \sum_{k=0}^{7} B_k^-(x,y)\}, \quad (1)$$

where

$$B_k^+(x,y) = \begin{cases} 1 & (I_{b_k^+}(x,y) - I(x,y) > 0) \\ 0 & (otherwise) \end{cases} \quad (2)$$

and

$$B_k^-(x,y) = \begin{cases} 1 & (I_{b_k^-}(x,y) - I(x,y) < 0) \\ 0 & (otherwise) \end{cases}. \quad (3)$$

The position of the reference pixels can be set by the mean or mode of the positions from multiple training images.

Although BPRRC, similarly to PISC and LBP, is robust against illumination changes, it is not robust against background movements because of its rigid background model using reference pixels $b_k^{\pm}(x, y)$.

3.2 Formulation of Probabilistic BPRRC

To increase the robustness against background movements, we introduce a probabilistic model into the BPRRC background model.

Let the reference pixels with the reach r in the direction k from a target pixel $BG(x, y)$ be $b_k^{\pm}(x, y, r)$, the range of reach r be R, and the count of b be $Num\{b\}$. In the training stage, Probabilistic BPRRC (PrBPRRC) stores $b_k^{\pm}(x, y, r)$, the distribution of the position of the reference pixels, by histogram models as shown in Fig. 2. In the detection stage, PrBPRRC detects changes as follows. The probability distribution of $b_k^{\pm}(x, y, r)$ is given by

$$prob(b_k^{\pm}(x,y,r)) = \frac{Num\{b_k^{\pm}(x,y,r)\}}{Num\{\sum_{r \in R} b_k^{\pm}(x,y,r)\}}, \quad (4)$$

and this can be calculated from the histogram of $b_k^{\pm}(x, y, r)$ learned in the training stage as Fig. 2. Next, PrBPRRC's codes of the input pixel $I(x, y)$ with the reach r and the direction k are given in the probabilistic form as

$$B_k^+(x,y,r) = \begin{cases} prob(b_k^+(x,y,r)) & (I_{b_k^+}(x,y,r) - I(x,y) > 0) \\ 0 & (otherwise) \end{cases} \quad (5)$$

and

$$B_k^-(x,y,r) = \begin{cases} prob(b_k^-(x,y,r)) & (I_{b_k^-}(x,y,r) - I(x,y) < 0) \\ 0 & (otherwise) \end{cases}. \quad (6)$$

Finally, by marginalizing Eq. (5) and (6) over reach r and direction k, the correspondence $B(x, y)$ is given by

$$B(x,y) = \frac{1}{16}\{\sum_{k=0}^{7}\sum_{r \in R} B_k^+(x,y,r) + \sum_{k=0}^{7}\sum_{r \in R} B_k^-(x,y,r)\}. \quad (7)$$

Now, the decision of the changes with Eq. (1)-(3) is replaced by probabilistic decision with Eq. (4)-(7). This formulation relaxes the decision of reference pixel position and makes PrBPRRC robust against background texture disturbances caused by background movements and foreground invasions.

4 Experiment

We compare the performance of several change detection methods with public datasets and show the superiority of our PrBPRRC. We use ATON Highway data [2], Karlsruhe traffic sequence data [3], and PETS

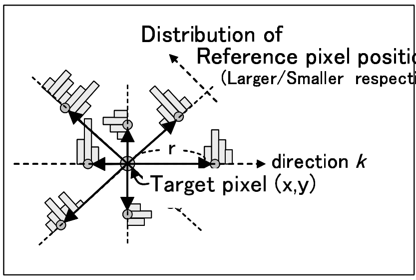


Figure 2: Schematic of the background model of Probabilistic BPRRC

2007 data [4]. We taught a ground truth for several images of each dataset: foreground objects such as moving cars and walking pedestrians as "foreground" (red in Fig. 3), obscure area such as shadows and crowds that exist at all times in the background training images as "don't care" (blue in Fig. 3), and other area as "background".

(a) ATON (b) Karlsruhe (c) PETS 2007

Figure 3: Samples of ground truth

We used 20∼40 frames for background training and 3∼5 frames for testing [1]. All the datasets contain background movements and foreground invasions such as moving cars, walking pedestrians, swaying trees, and falling snow. The PETS 2007 data also contain large illumination changes between S1 sequence for training and S0 sequence for testing.

The ROC (Receiver Operating Characteristic) curves are shown in Fig. 4. An ROC curve further toward the bottom-left of the diagram means better performance. PrBPRRC (● in Fig. 4) is consistently better than BPRRC-mean (△ in Fig. 4) with reference pixels defined by the mean of multiple training images and BPRRC-mode (▽ in Fig. 4) with reference pixels defined by the mode of multiple training images. Though MoG/Histogram (× in Fig. 4) on ATON Highway I and PTESC (□ in Fig. 4) on Karlsruhe-stau02 are slightly better than PrBPRRC, they are much worse than PrBPRRC on other data. PrBPRRC combined with PTESC (○ in Fig. 4) shows better performance than PrBPRRC because they complement each other: PrBPRRC is based on the texture in a broad region and PTESC is based on the texture in a local region.

[1]The description of the experimentation data is as follows: we used (a) 30 frames at the beginning of the sequence for background training and 4 frames with 100 frame interval at the end of the sequence for testing on ATON highway I/II data, (b) 20 frames with 20 frame interval for background training and 3 frames with 100/200 frame interval for testing on Karlsruhe-dtneu_schnee/stau02 data, (c) 40 frames with 100 frame interval from S1 sequence for background training and 5 frames with 500 frame interval from S0 sequence for testing on PETS 2007 cam4 data. The sequence of Karlsruhe-dtneu_schnee is so short that the ranges of training and testing sequences are overlapped but the frames are separate. The sequence of Karlsruhe-stau02 is reversed because cars stop at the crossing at the beginning of the sequence and then start to move.

Some typical results of change detection are shown in Fig. 5. The parameters of each method such as texture threshold and texture size are the same for all the datasets. In contrast to former methods, PrBPRRC is stable for various datasets with the same parameters.

All the results above show that PrBPRRC is more stable than former methods against data disturbances and parameter setting.

5 Conclusion

In this paper, we proposed PrBPRRC, the extension of the BPRRC, which preserves BPRRC's robustness against illumination changes and adds the robustness against background movements.

We introduced a probabilistic background texture model into BPRRC. Our new method learns the distribution of background texture based on the intensity differences between target pixel and reference pixels, and detects changes with a probabilistic decision based on the texture distribution. It enables learning of a probabilistic background from the training images including background movements and foreground invasions such as moving cars, walking pedestrians, swaying trees, and falling snow.

We evaluated several change detection methods with ATON Highway data, Karlsruhe traffic sequence data, and PETS 2007 data and showed the superiority of our PrBPRRC in terms of stability against data disturbances and parameter setting.

In future work, we intend to improve the performance by introducing color texture information into the PrBPRRC model.

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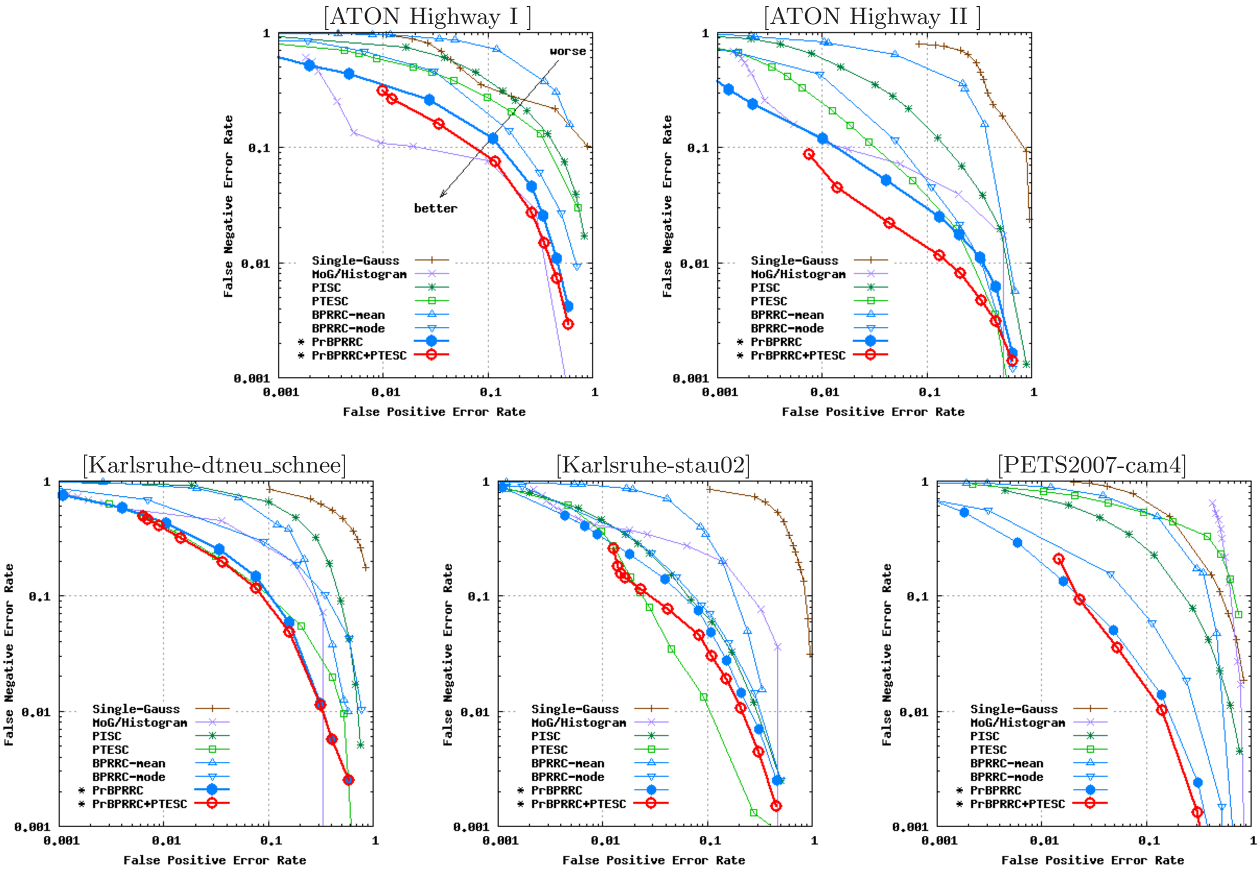
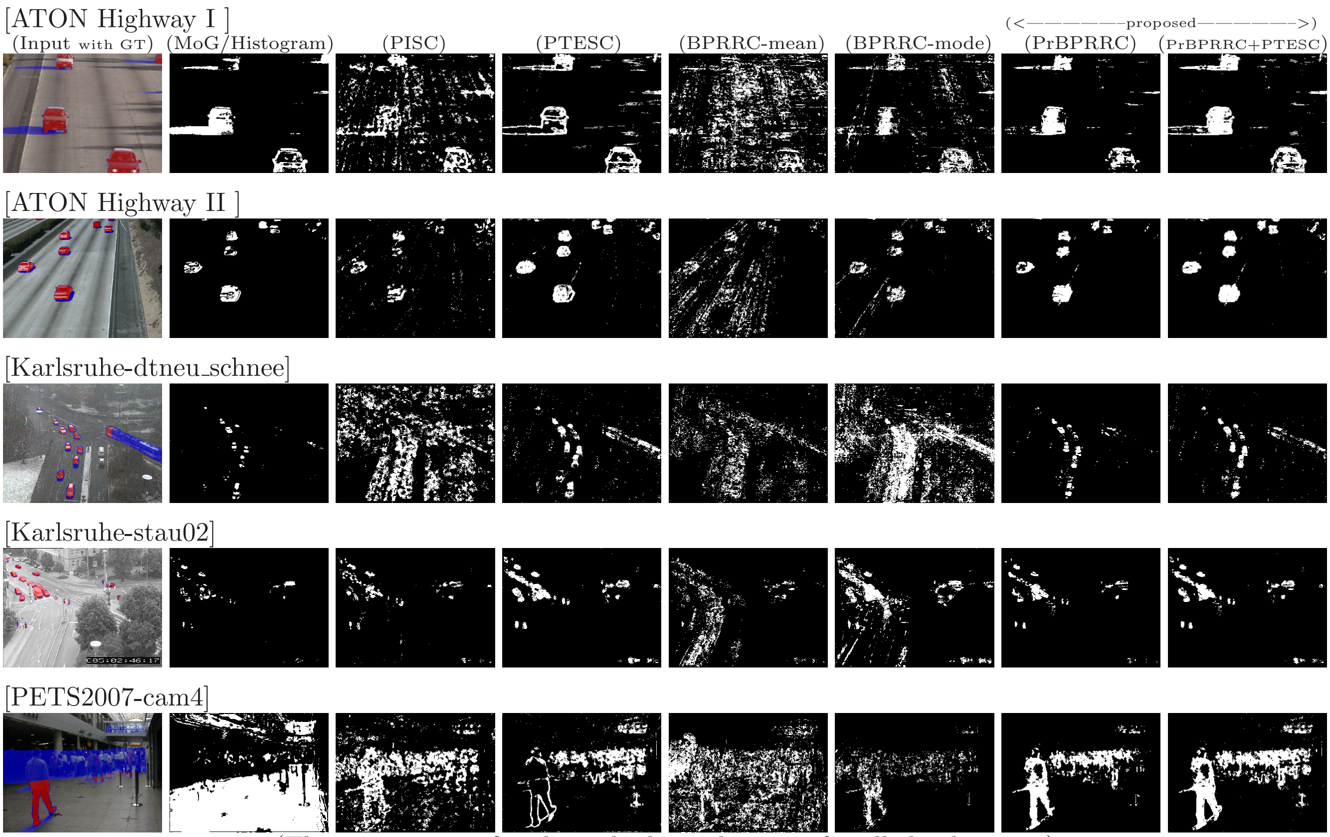


Figure 4: ROC curves



(The parameters of each method are the same for all the datasets.)

Figure 5: Typical results of change detection for several datasets