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

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SUMMARY This paper presents Probabilistic Bi-polar Radial Reach Correlation (PrBPRRC), 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 including foreground invasions such as moving cars, walking people, swaying trees, and falling snow. We show the superiority of PrBPRRC in the environment with illumination changes and background movements by using three public datasets and one private dataset: ATON Highway data, Karlsruhe traffic sequence data, PETS 2007 data, and Walking-in-a-room data.
key words: *change detection, background detection, Probabilistic BPRRC, robust, illumination changes, background movements*

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 detections from background region (Fig. 1).

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 the rigid texture model.

We propose Probabilistic BPRRC (PrBPRRC), an extension of BPRRC, that preserves BPRRC's robustness against illumination changes and adds the robustness against background movements [2]. 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 PrBPRRC with three public datasets and one private dataset: ATON Highway data [3], Karlsruhe traffic sequence data [4], PETS 2007 data [5], and Walking-in-a-room data.

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

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

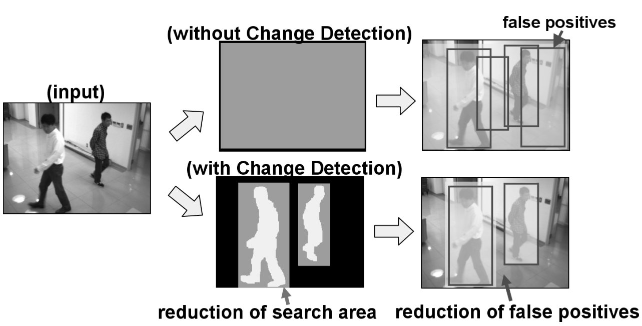

Fig. 1 Schematics of the effectiveness of change detection for human detection. Change detection reduces search area and false positives of human detection.

2. Related Works

Many change detection methods have been proposed. Generally, they calculate the probability distribution of the input pattern from training images with the background model, and then detect changes from the test image according to the posterior probability. Figure 2 and Table 1 show the schematics of the background models of change detection explained below and a comparison of them, respectively.

One of the simplest background models is the single Gaussian model that models each pixel intensity with a single Gaussian distribution (Fig. 2 (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) [6] that uses multiple Gaussian distributions to model multiple

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Table 1 Comparison of background models for change detection.

background model		robust against illumination changes	robust against background movements
pixel -intensity -based model	(a) Single Gaussian (average background)	×	×
	(b) Mixture of Gaussian (MoG, GMM)	×	○
	(c) Pixel-intensity Histogram	×	○
texture -based model	(d) PISC/LBP/PTESC	○	×
	(e) BPRRC	○	×
	(f) PrBPRRC	○	○

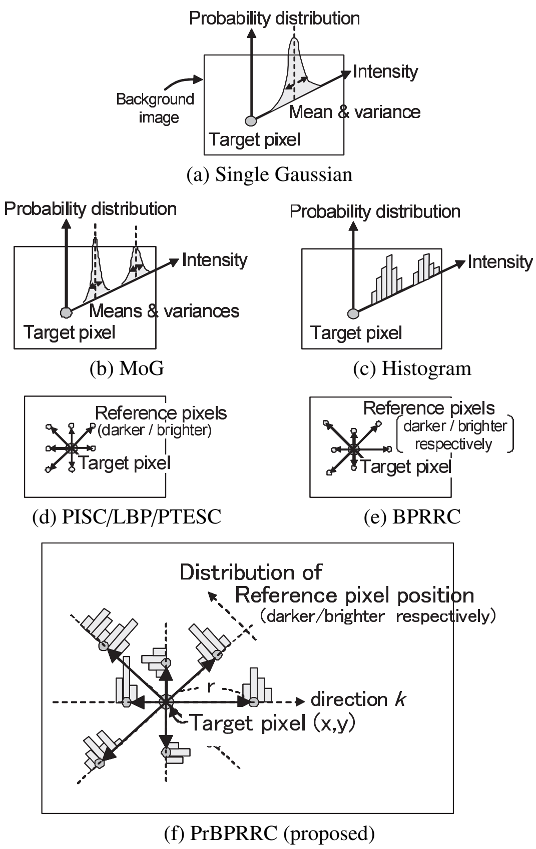


Fig. 2 Schematics of the background models of change detection methods.

background intensity distributions caused by ripples on water surface and flickering of the display (Fig. 2 (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 [7] (Fig. 2 (c)). Because, in contrast to the Gaussian model, it doesn't assume any parametric models, it can model arbitrary intensity distributions.

The pixel-intensity-based models such as MoG and the histogram model are not robust against illumination changes (Table 1 (a)–(c)) 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) [8] and Heikkilä et al. proposed Local Binary Pattern (LBP) [9]; they encode the intensity differences between target pixel and surrounding reference pixels as 0/1 binary code (Fig. 2 (d)). Yokoi proposed Peripheral TErnary Sign Correlation (PTESC) [10] 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 (Table 1 (d)), 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.

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. 2 (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.

Figure 3 shows the schematics of the process of BPRRC. In the training stage (Fig. 3 (a)), 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 $b_k^+(x, y)$ $(k = 0, \ldots, 7)$. 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 (Fig. 3 (b)), in an input image I, it compares intensity differ-

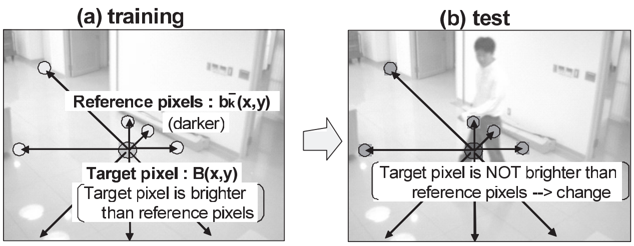


Fig. 3 Schematics of the process of BPRRC.

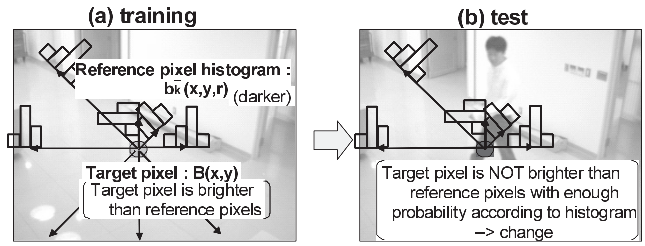


Fig. 4 Schematics of the process of PrBPRRC.

ences 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:

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

where

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

and

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

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 (Table 1 (e)) because of the 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 (Fig. 2 (f)) [2]. Figure 4 shows the schematics of the process of PrBPRRC.

Let the range of reach r that means the distance from a target pixel to the reference pixel be R, the reference pixels with the reach r in the direction k from a target pixel $BG(x, y)$ be $b_k^\pm(x, y, r)$, and the count of b be $Num\{b\}$. In the training stage (Fig. 4 (a)), Probabilistic BPRRC (PrBPRRC) searches reference pixels with positive/negative intensity differences above a threshold from $Bg(x, y)$ in the same way as BPRRC and stores them as $b_k^\pm(x, y, r)$, the distribution of the position of the reference pixels, by histogram models. If there are background movements such as walking people and swaying trees, all the disturbances of reference pixels caused by them are modeled by the histogram models. In the detection stage (Fig. 4 (b)), PrBPRRC detects changes as follows. The probability distribution of $b_k^\pm(x, y, r)$ is given by

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

and this can be calculated from the histogram of $b_k^\pm(x, y, r)$ learned in the training stage. 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

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

and

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

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

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

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

Figure 5 shows the schematics of the robustness of PrBPRRC. In BPRRC, the background model is learned with static model in the training stage; the positions of reference pixels are set by the mean or mode of those from multiple training images. Though the reference pixel was darker than the target pixel in a training stage (Fig. 5 (a-1)), it is no darker than the target pixel in the test stage if the tree sways (Fig. 5 (a-2)). Therefore, the system falsely decides there is a change in the target pixel. In PrBPRRC, on the contrary, the background model is learned with a flexible model in the training stage; the positions of reference pixels are modeled by the histogram from multiple training images (Fig. 5 (b-1)). Because the histogram models the distribution of the positions of reference pixels that distribute according to the tree swaying in the training stage, the system recognizes the position of the reference pixel that is darker than the target pixel in the test stage has enough probability according to the histogram and therefore the system correctly decides there is no change in the target pixel (Fig. 5 (b-2)).

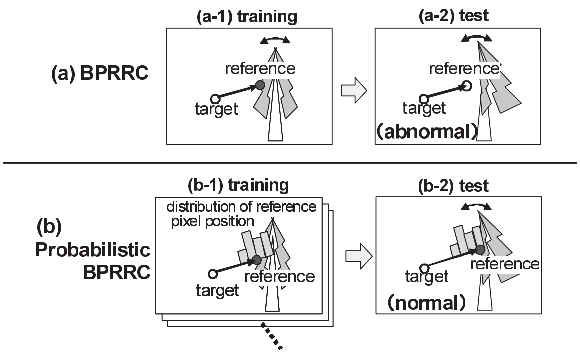


Fig. 5 Comparison between BPRRC and PrBPRRC.

4. Experiment

In this section we evaluate the performance of the change detection methods described in Sects. 2 and 3. The detection accuracy is evaluated in Sect. 4.1 and the detection speed in Sect. 4.2. The results show the superiority of the proposed PrBPRRC in terms of detection accuracy with acceptable processing time.

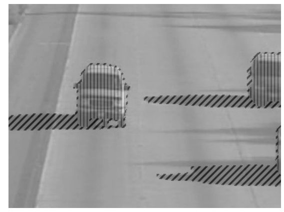
4.1 Detection Accuracy

We compared the detection accuracies of change detection methods with four datasets. We used ATON Highway data [3], Karlsruhe traffic sequence data [4], PETS 2007 data [5], and private Walking-in-a-room data. Figure 6 shows the samples of each dataset with ground truth annotations, which we explain later. ATON data and Karlsruhe data include foreground invasion of passing cars and Karlsruhe-dtneu_schnee data includes falling snow. PETS 2007 data includes foreground invasion of walking and waiting people in the training images and illumination changes in the test images. The private Walking-in-a-room data is a short movie of walking people in a room that includes foreground invasion of walking people in the training images and illumination changes in the test images. Figure 7 shows the samples of disturbances such as foreground invasions and illumination changes.

We used 20~40 frames for background training and 3~5 frames for testing†. All the test images have ground truth annotations: foreground objects such as moving cars and walking people as "foreground (FG)" (vertical hatches in Fig. 6), obscure area such as shadows and crowds that exist at all times in the background training images as "don't care" (diagonal hatches in Fig. 6), and other area as "background (BG)". False positive error rate (FPR) and false negative error rate (FNR) are defined as follows:

$$FPR = \frac{num\_of\_falsely\_detected\_BG\_pixels\_as\_FG}{num\_of\_BG\_pixels\_in\_the\_ground\_truth},$$

$$FNR = \frac{num\_of\_falsely\_detected\_FG\_pixels\_as\_BG}{num\_of\_FG\_pixels\_in\_the\_ground\_truth}.$$



(a) ATON

(b) Karlsruhe

(c) PETS 2007

(d) Walking-in-a-room

Fig. 6 Samples of datasets with ground truth annotations.

[(c) PETS 2007]
(training) (test)

[(d) Walking-in-a-room]
(training) (test)

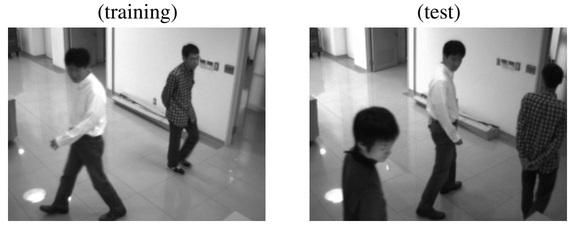


Fig. 7 Samples of disturbances in the datasets.

The ROC (Receiver Operating Characteristic) curves are shown in Fig. 8. An ROC curve further toward the bottom left of the diagram indicates better performance.

†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, and (d) 30 frames with 6-frame interval for background training and 3 frames with 80-frame interval for testing on Walking-in-a-room 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.

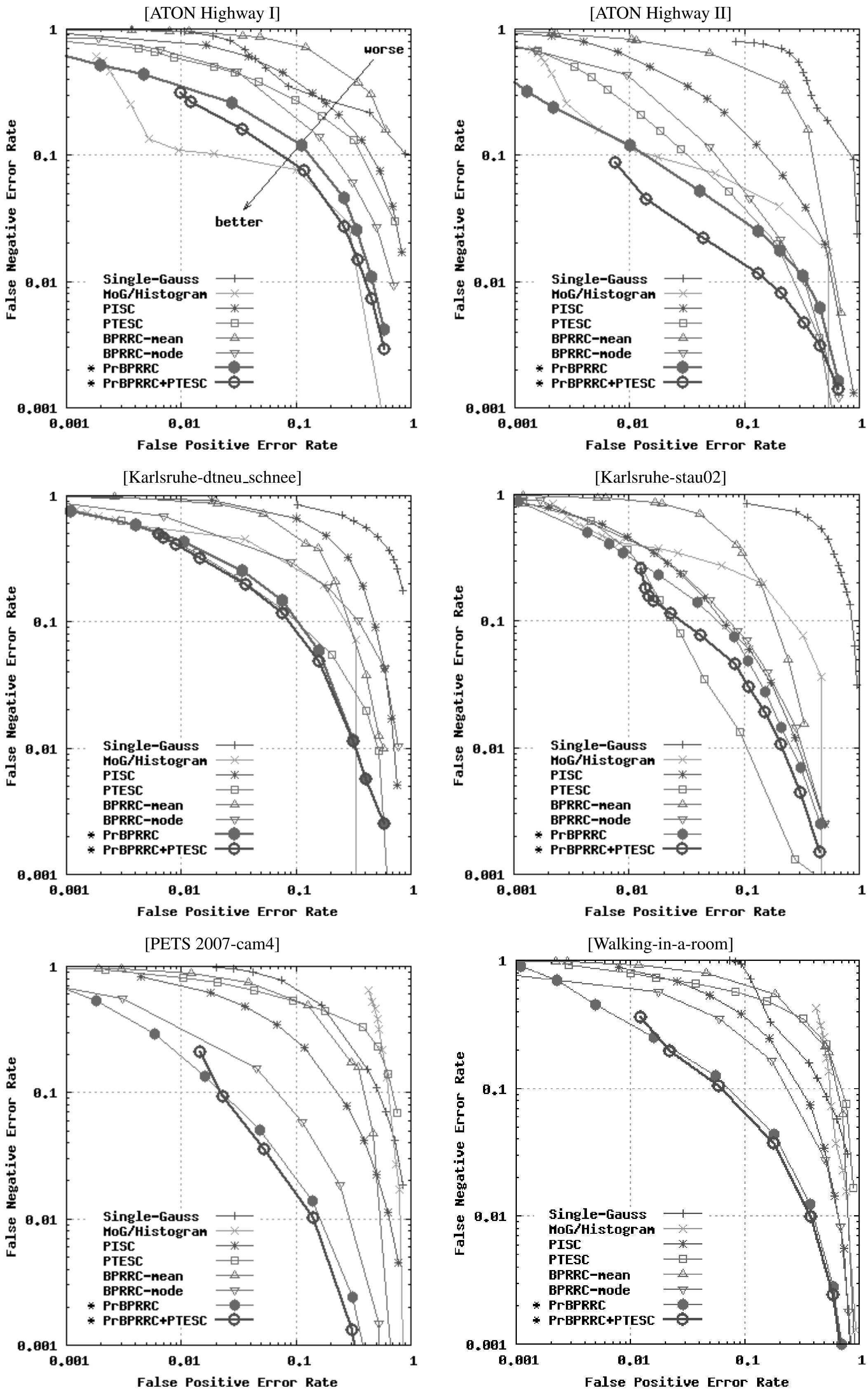
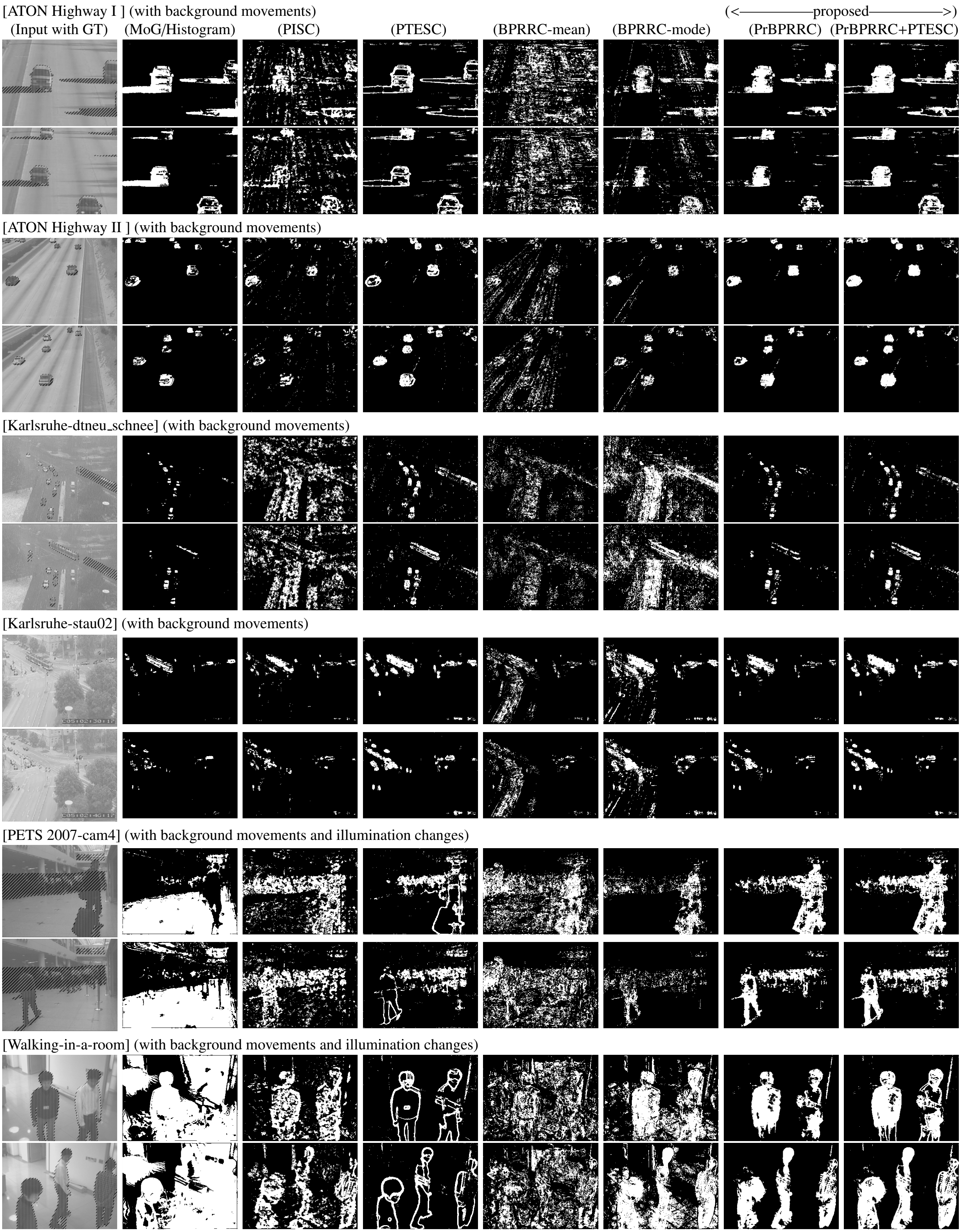
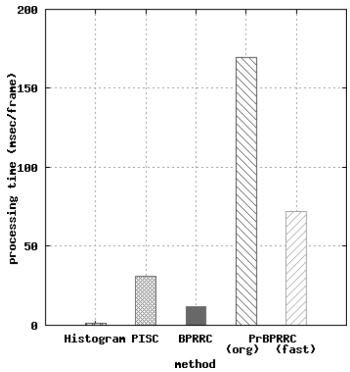


Fig. 8 ROC curves.



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

Fig. 9 Typical results of change detection for several datasets.



(with no optimization such as SIMD operation)

Fig. 10 Average processing time for one frame of PETS 2007 data.

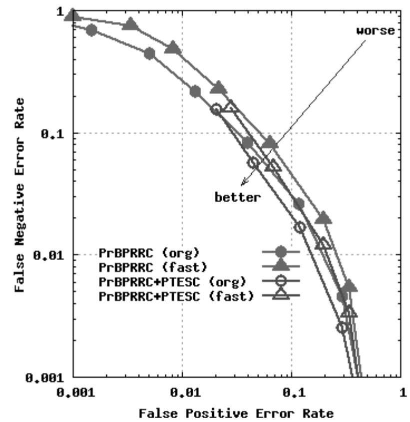


Fig. 11 ROC curves of two versions of PrBPRRC on PETS 2007 data.

PrBPRRC (● in Fig. 8) is consistently better than BPRRC-mean (△ in Fig. 8) with reference pixels defined by the mean of multiple training images and BPRRC-mode (▽ in Fig. 8) with reference pixels defined by the mode of multiple training images. Though MoG/Histogram (× in Fig. 8) on ATON Highway I and PTESC (□ in Fig. 8) on Karlsruhe-stau02 are slightly better than PrBPRRC, they are much worse than PrBPRRC on other data. We combined PrBPRRC with PTESC using OR operation (○ in Fig. 8). The combined results show 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.

Some typical results of change detection are shown in Fig. 9. The parameters of each method such as texture threshold (= 10) and texture size (= 5) are the same for all the datasets. In contrast to former methods, PrBPRRC is stable for various datasets with the same parameters.

4.2 Detection Speed

We also compared the detection speed of change detection methods. Figure 10 shows the average processing time of each detection method for one frame of PETS 2007 data†. In the experiment we evaluated two versions of PrBPRRC: the original PrBPRRC evaluated in the previous section using 51-reach histogram (shown as “org” in Fig. 10) and the faster PrBPRRC using 12-reach histogram (shown as “fast” in Fig. 10). The figure such as 51 and 12 is the number of the reach candidates r to check the positive/negative intensity differences. We searched the reference pixels only with limited reaches such as “$r = 1, 2, 4, 6, \ldots$” for speed-up. Figure 11 shows the ROC curves of the two versions of PrBPRRC on PETS 2007 data.

Though the original PrBPRRC requires more than 10 times more processing time than BPRRC (Fig. 10), the faster PrBPRRC requires approximately five times more processing time than BPRRC and is acceptable in view of its better performance than BPRRC. The detection accuracy of the faster PrBPRRC is slightly worse than that of the original PrBPRRC (Fig. 11) because it uses sparser histogram for the position of reference pixels in Fig. 2 (f); however, the decrease in accuracy is small enough to be acceptable.

4.3 Total Performance

The evaluations in Sects. 4.1 and 4.2 show that, compared to former methods, the proposed PrBPRRC realizes better performance with acceptable processing time. The evaluation of detection accuracy in Sect. 4.1 shows that PrBPRRC is more stable than former methods against data disturbances and parameter setting. Though the evaluation of detection speed in Sect. 4.2 shows that PrBPRRC requires more processing time than BPRRC, the processing time of PrBPRRC can be reduced up to five times more than that of BPRRC by using a small number of reach candidates. The loss of detection accuracy using a small number of reach candidates is small enough to be acceptable and the processing time of the method is also acceptable because it realizes 10 fps processing.

5. Conclusion

In this paper, we proposed PrBPRRC, an extension of BPRRC, that 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 people, swaying trees, and falling snow.

We evaluated several change detection methods with ATON Highway data, Karlsruhe traffic sequence data, PETS 2007 data, and private Walking-in-a-room data and showed the superiority of PrBPRRC in terms of stability against data

†On other datasets we obtained similar results.

disturbances and parameter setting.

In future work, we intend to improve the performance by introducing color texture information into the PrBPRRC model. Generally, color information is informative but not robust against illumination changes. PrBPRRC's robustness against illumination changes will be able to suppress the instability of color and utilize its fruitful information for change detection.

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