13-14

MVA2007 IAPR Conference on Machine Vision Applications, May 16-18, 2007, Tokyo, JAPAN

Illumination-robust Change Detection Using Texture Based Features

Kentaro Yokoi
Corporate Research and Development Center, TOSHIBA Corporation,
1, Komukai-Toshiba-Cho, Saiwai-Ku, Kawasaki-Shi, 212–8582 Japan
E-mail: kentaro.yokoi@toshiba.co.jp

Abstract

We propose a change detection method which is robust against illumination change and requires little background learning as a result of using texture based features. We propose Peripheral TErnary Sign Correlation (PTESC) which is robust against illumination changes by using $-1/0/1$ ternary code for encoding the intensity difference between pixels in texture, and combine it with Bi-polar Radial Reach Correlation (BPRRC) which yields high detectability in a region with little texture. We show that our method detects changes with fewer false positives and false negatives under illumination changes compared with former methods.

1 Introduction

Change detection is one of the most basic processes in image recognition, consequently many methods have been proposed particularly for surveillance [1]. Gait recognition and motion capture in particular require a method with fewer false positives and false negatives because these applications need the precise human silhouette [2][3]. Motion capture also requires a method requiring little background learning as it can not learn the background in advance, unlike a surveillance system. We design a method requiring little background learning and yielding fewer false positives and false negatives by using texture features which are robust against illumination changes.

2 Former Methods

Various methods have been proposed for change detection.

The average background subtraction method learns an average background from background images, and detects changes by comparing it with input images. This method is weak with respect to illumination change. To compensate, methods which normalize intensities in a whole image or a local region and learn background under various illumination have been proposed [1].

Eigen background method [4][5] uses an eigen background subspace which learns illumination changes and sensor noises by principal component analysis and compares it with input images. This method is not robust against illumination changes in the case of little background learning.

Peripheral Increment Sign Correlation (PISC) [6] compares a target pixel $Bg(x, y)$, with the coordinates (x, y) in a background image Bg, with its 2-pixel-separated peripheral pixels $Bg(x+2, y), Bg(x+2, y+1), \cdots, Bg(x+2, y-1)$. And then it encodes the intensity differences as 0/1 peripheral increment sign $p_k(x, y)$ $(k = 0, ..., 15)$ which is 1 in the case that peripheral pixel has a higher intensity than the target pixel and 0 otherwise. It also encodes $p'_k(x, y)$ in an input image in the same way and detects changes based on the correspondence $P(x, y)$ between the codes.

$$P(x, y) = \frac{1}{16} \sum_{k=0}^{15} P_k(x, y) \tag{1}$$

$$P_k(x, y) = p_k(x, y)p'_k(x, y) + (1-p_k(x, y))(1-p'_k(x, y))$$

This method is robust against illumination changes because it encodes illumination-robust intensity difference between a pixel and its peripheral pixels, however, it can not detect changes such as an untextured object in front of a plain background with different intensity. Heikkilä et al. proposed Local Binary Pattern (LBP) [7][8] which generalized PISC on the position of peripheral pixels and it has the same property as PISC.

Bi-polar Radial Reach Correlation (BPRRC) [9] searches over reference pixels with positive intensity difference above a threshold from a pixel $Bg(x, y)$ in 8 directions in a background image Bg and saves the position as $b_k^+(x, y)$ $(k = 0, ..., 7)$. In the same way it searches over reference pixels with negative intensity difference and saves the position as $b_k^-(x, y)$. Then in an input image I, it compares intensity differences between pixel $I(x, y)$ and its 16 reference pixels $I_{b_k^\pm}(x, y)$ and detects changes based on the correspondence $B(x, y)$ between background and input.

$$B(x, y) = \frac{1}{16}\{\sum_{k=0}^{7} B_k^+(x, y) + \sum_{k=0}^{7} B_k^-(x, y)\} \tag{2}$$

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

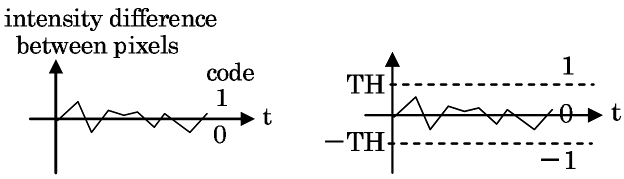
$$B_k^-(x, y) = \begin{cases} 1 & (I_{b_k^-}(x, y) - I(x, y) < 0) \\ 0 & (otherwise) \end{cases} \tag{3}$$

This method, similarly to PISC and LBP, is robust against illumination changes, however, has many false negatives because it detects only large changes such as the reverse of intensity difference between a pixel and its reference pixels.

3 Proposed Method

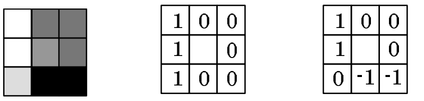
3.1 Peripheral TErnary Sign Correlation (PTESC)

PISC and LBP referred in section 2 encodes the intensity difference between a pixel and its peripheral pixels as $0/1$ binary code. As shown in Figure 1(a), this causes false positives because the code is reversed easily with slight intensity changes in a region with small intensity differences, namely plain region. Plain region often occupies large amount of images, so that stabilizing in plain region is important. Therefore we proposed Peripheral TErnary Sign Correlation (PTESC) [10] which stabilizes the encoding by using $-1/0/1$ ternary code (Figure 1(b)). The schematic of encoding is shown in Figure 2[1].



(a) PISC (b) PTESC

Figure 1: comparison of PISC and PTESC



input PISC PTESC

Figure 2: schematic of PISC and PTESC encoding

This method encodes the intensity differences by $-1/0/1$ ternary code based on a threshold TH.

$$p_0(x,y) = \begin{cases} 1 & (\quad TH < Bg(x+2,y) - Bg(x,y) \qquad) \\ 0 & (-TH \leq Bg(x+2,y) - Bg(x,y) \leq \ TH) \\ -1 & (\qquad Bg(x+2,y) - Bg(x,y) < -TH) \end{cases}$$
$$\vdots \tag{4}$$
$$p_{15}(x,y) = \begin{cases} 1 & (\quad TH < Bg(x+2,y-1) - Bg(x,y) \qquad) \\ 0 & (-TH \leq Bg(x+2,y-1) - Bg(x,y) \leq \ TH) \\ -1 & (\qquad Bg(x+2,y-1) - Bg(x,y) < -TH) \end{cases}$$

In the case that small intensity changes have happened in a plain region, PTESC encodes them as 0 stably and does not cause any false positives. Although PTESC can be unstable in a region with intensity differences around TH and $-TH$, such a region is rare enough that PTESC is generally stable.

[1] We use distant pixels as peripheral pixels for PISC and PTESC, not 2-pixel-separated pixels like original PISC.

3.2 Combination of PTESC and BPRRC

PTESC can not detect an untextured object in front of a plain background with different intensity from object, because it detects the texture differences. BPRRC, on the other hand, can detect changes in such a situation because it selects reference pixels $b_k^{\pm}(x,y)$ from distant textured region. If a significant enough intensity change, by comparison to a reference pixel set, has occurred to the target pixel, it can be detected. But BPRRC can detect only relatively large changes such as the reverse of intensity differences so that many false negatives can be occurred.

We propose a method which can detect changes under various texture environment by combining PTESC, which has high detectability under textured background or textured object, and BPRRC, which has high detectability under untextured environment.

As also shown in the experiments of the next section, PTESC and BPRRC are mutually complementary because PTESC is based on the intensity differences in a local region and BPRRC is based on those in a broad region. Furthermore, the combination introduces few false positives because they both have few false positives because of their illumination robustness. We combine these two results, $Result_{PTESC}(x,y)$ and $Result_{BPRRC}(x,y)$, and then detect changes as follows.

$$Result(x,y) = \begin{cases} change & (Result_{PTESC}(x,y) = change \ \ or \\ & \ Result_{BPRRC}(x,y) = change) \\ const. & (otherwise) \end{cases} \tag{5}$$

4 Experiment

We compared the performance of the methods described above with images obtained from an office environment. We set two illumination environments (A: illumination on, B: illumination off) by switching on and off fluorescent lights situated on the ceiling. Ten images[2] (2 frame/sec.) under illumination A are used for background learning and 40 images each (2 frame/sec.) under two illumination environments are used for test input. Ground truth is defined manually and used for evaluating the detection correctness. Performance is evaluated by False Negative Error Rate (FNER), the rate of the person region which is not detected, and False Positive Error Rate (FPER), the rate of the background region which is falsely detected as object.

$$FNER = \frac{area\_of\_false\_negative\_error}{true\_area\_of\_person} \tag{6}$$

$$FPER = \frac{area\_of\_false\_positive\_error}{true\_area\_of\_background} \tag{7}$$

The results are shown in Figure 3-5. In the figures "Avg" means average background subtraction, "Avg-norm" means average background subtraction with intensity normalization in a whole image, "PCA" means eigen background, and "PCA-norm" means eigen background with intensity

[2] Only 1 image is enough for PTESC learning, but we use 10 images for eigen background learning.

normalization in each block. Figure 3 shows ROC (Receiver Operator Characteristic) curve which plots FPER and FNER in log scale with various threshold. Plots at the lower left mean better performance. Figure 4-5 show the result of change detection and FNER/FPER under a threshold (each method uses the same threshold in all experiments).

ROC curve shows that our method (PTESC+BPRRC) has the highest detectability under almost all conditions. Detection examples also show it qualitatively.

We applied the same experiment to the PETS-2001 and PETS-ICVS data distributed by IEEE International Workshop on Performance Evaluation of Tracking and Surveillance[3]. The same thresholds as the experiments of Figure 4-5 are used. Some of the typical results are shown in Figure 6-8. Our method shows almost the best performance with PETS-2001 and PETS-ICVS data too. Proper detection results can be gained with the same threshold setting for different data, therefore this shows that our method is not sensitive to the threshold setting.

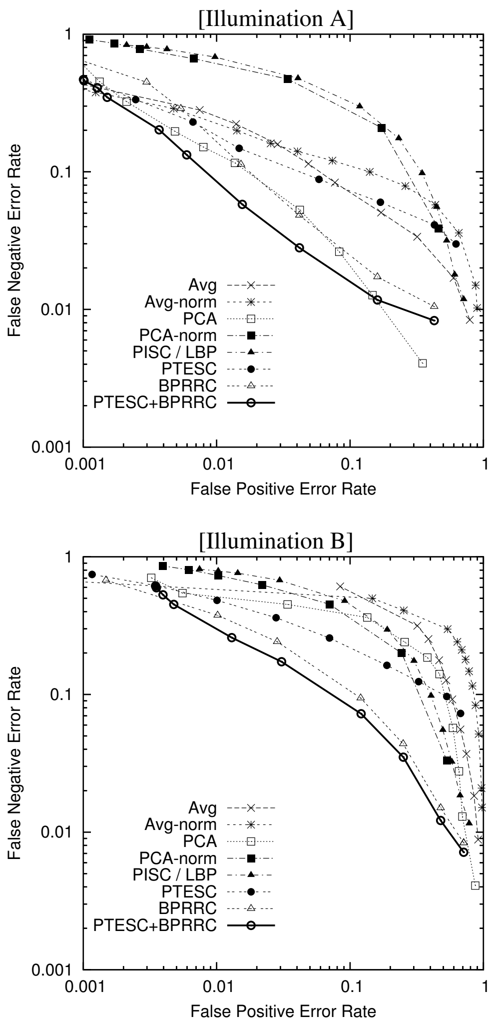


Figure 3: ROC curve

[3]http://www.cvg.rdg.ac.uk/PETS2001/, http://www.cvg.cs.rdg.ac.uk/PETS-ICVS/

5 Conclusion

In this paper, we proposed an illumination robust change detection method based on texture features. Our method detects changes with less background learning and has fewer false negatives and false positives than previous methods, therefore it can be used not only for surveillance but for gait recognition and motion capture which require the precise human silhouette as input.

We required little background learning as a result of using texture features, which are robust against illumination changes. We proposed PTESC (Peripheral TErnary Sign Correlation) which encodes the intensity difference with $-1/0/1$ ternary code, which stabilize PISC (Peripheral Increment Sign Correlation) and LBP (Local Binary Pattern) which encodes the intensity difference with $0/1$ binary code. PTESC stabilizes the detection because it encodes 0 stably in the case that intensity noise has happened in a plain region, where PISC and LBP codes change $0/1$ unstably.

We also propose combination of PTESC, which has high detectability under textured background or textured object, and BPRRC (Bi-polar Radial Reach Correlation) , which has high detectability under untextured environment. PTESC and BPRRC are mutually complementary and individually produce fewer false positives, so that combination of them achieves both fewer false negatives and fewer false positives.

We compared the performances of our method and former methods such as average background subtraction and eigen background with images under an office environment. The results showed that our method had the best performance among them, similarly to the experiment with PETS-2001 and PETS-ICVS data.

We will improve its performance with color information and color texture in the near future.

References

[1] K. Toyama, J. Krumm, B. Brumitt, and B. Meyers. Wallflower: Principles and practice of background maintenance. *Proceedings of the 7th IEEE International Conference on Computer Vision (ICCV 1999)*, pp. 255–261, Sep. 1999.

[2] J. N. Carter M. S. Nixon. Automatic gait recognition. *Proceedings of the Sixth IEEE International Conference on Automatic Face and Gesture Recognition*, pp. 139–144, May 2004.

[3] T. B. Moeslund and E. Granum. A survey of computer vision-based human motion capture. *Computer Vision and Image Understanding*, Vol. 81, No. 3, pp. 231–268, Mar. 2001.

[4] N. M. Oliver, B. Rosario, and A. P. Pentland. A bayesian computer vision system for modeling human interactions. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 22, No. 8, pp. 831–843, Aug. 2000.

[5] M. Seki, H. Fujiwara, and K. Sumi. A robust background subtraction method for changing background. *Proceedings of the fifth IEEE Workshop on Applications of Computer Vision*, pp. 207–213, Dec. 2000.

[6] Y. Satoh, S. Kaneko, and S. Igarashi. Robust object detection and segmentation by peripheral increment sign correlation image. *Systems and Computers in Japan, John Wiley & Sons*, Vol. 35, No. 9, pp. 70–80, Jun. 2004.

[7] M. Heikkilä, M. Pietikäinen, and J. Heikkilä. A texture-based method for detecting moving objects. *Proceedings of the British Machine Vision Conference (BMVC 2004)*, Vol. 1, pp. 187–196, 2004.

[8] M. Heikkilä and M. Pietikäinen. A texture-based method for modeling the background and detecting moving objects. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 28, No. 4, pp. 657–662, April 2006.

[9] Y. Satoh and K. Sakaue. Robust background subtraction based on bi-polar radial reach correlation. *Proceedings of the IEEE International Conference on Computers, Communications, Control and Power Engineering (TENCON05)*, pp. 998–1003, Nov. 2005.

[10] K. Yokoi. Illumination-robust change detection using texture based features (in japanese). *Meeting on Image Recognition and Understanding 2006 (MIRU 2006)*, No. IS1-2, pp. 322–327, July 2006.

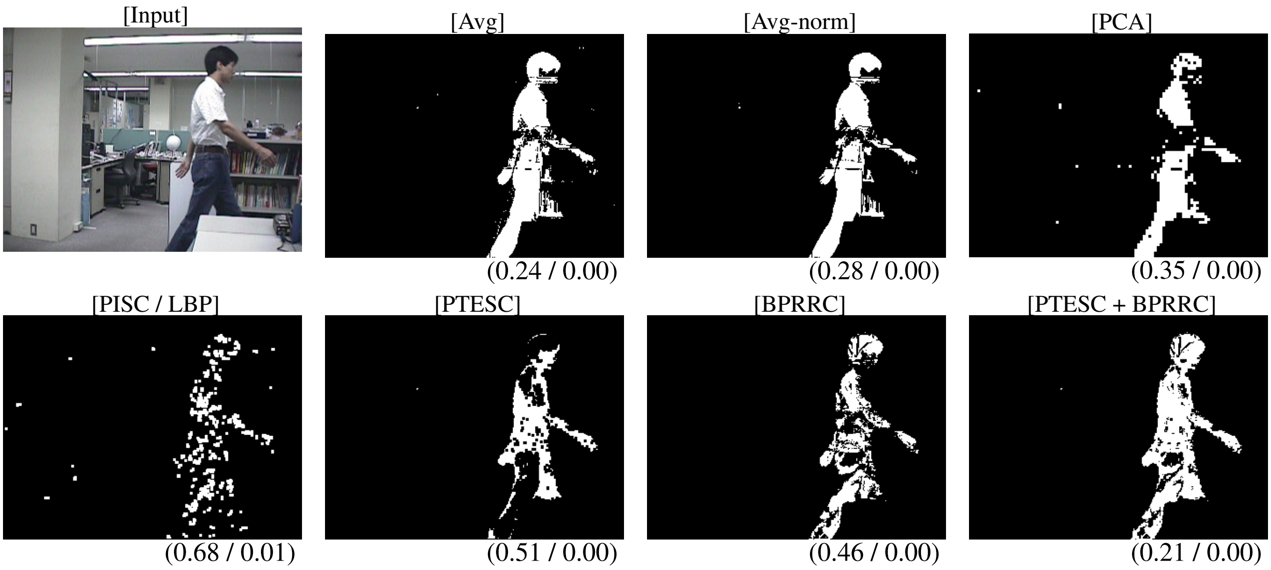


Figure 4: detection result under Illumination A (FNER / FPER)

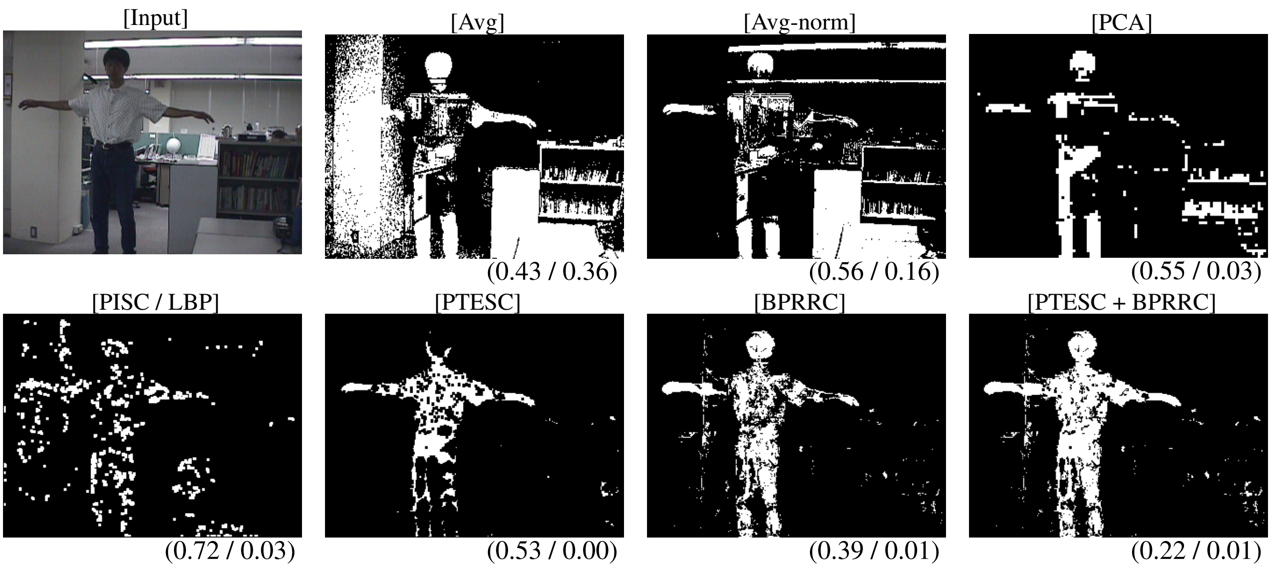


Figure 5: detection result under Illumination B (FNER / FPER)

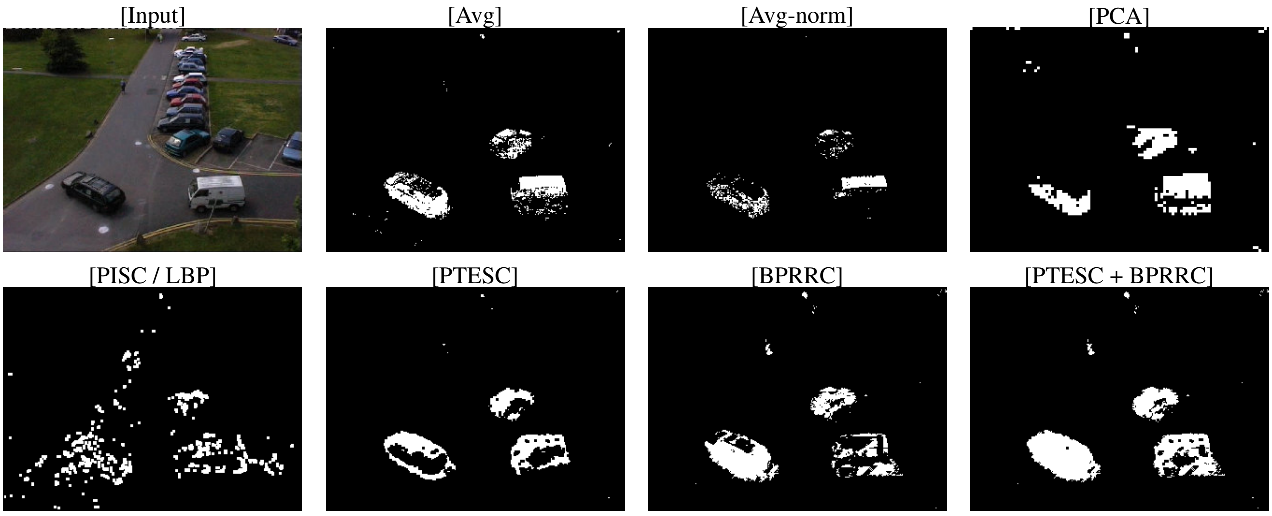


Figure 6: detection result of PETS-2001 Dataset1 Camera2

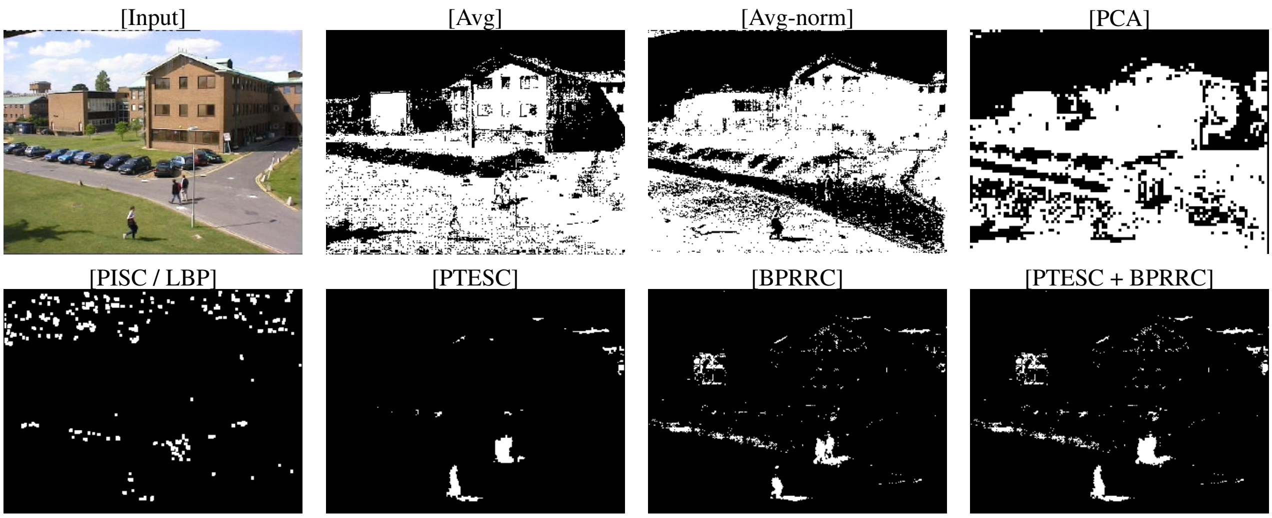


Figure 7: detection result of PETS-2001 Dataset3 Camera1 (extreme illumination change)

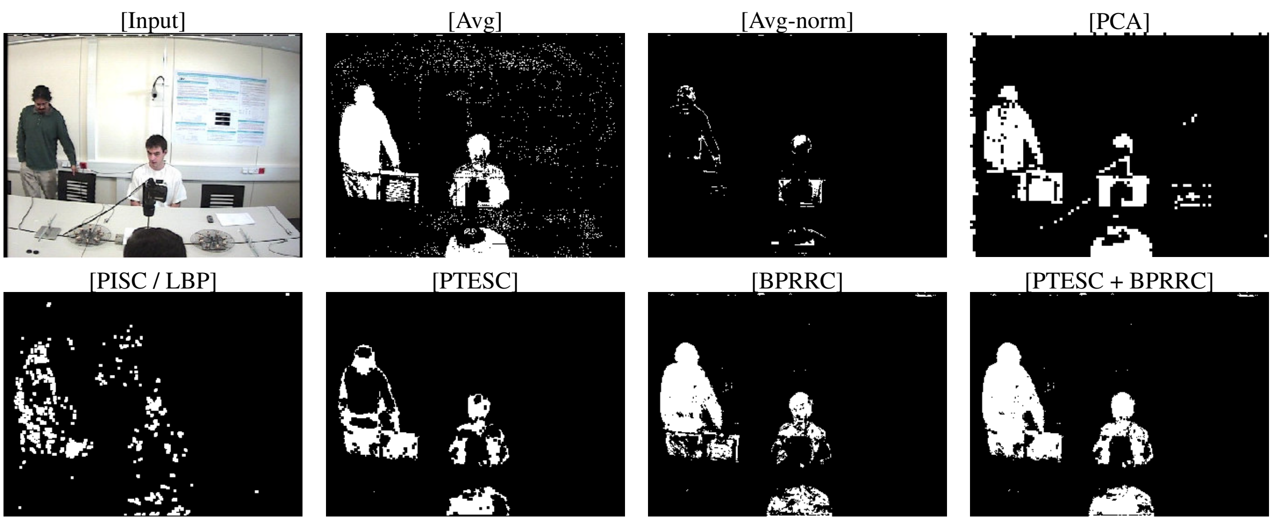


Figure 8: detection result of PETS-ICVS-2003 scenario B