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# DETECTION Background Subtraction Technique *As Review*

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## Block-based Background Subtraction

***Abstract***

**This paper presents an approach to background subtraction based on rectangular regions (blocks). The general principle is to successively divide the image into blocks and detect foreground pixels based on the colour histogram and the variance between pixels of the blocks. Then, the classic Gaussian Mixture background subtraction method is applied to refine the detected foreground. Results show that this approach reduces false positives by filtering noise coming from small motion as it is based on groups of pixels instead of on individual pixels.**

### *Introduction*

Motion detection is a crucial task in many computer vision applications, such as robotics, video monitoring, and action recognition. Several approaches to motion detection are based on background subtraction. The fundamental principle of background subtraction is to build a background model of an empty scene, and then compare that model with the current image. The difference forms the moving objects. However, irrelevant pixels can be detected as foreground (shadow, image noise, dynamic scene element, etc.). Thus, a background subtraction method has to be able adapt to different conditions in a video sequence and to a changing background. Most background subtraction methods label pixels as background or foreground based on pixel by pixel decision such as Single Gaussian (SG) [4], Kernel Density Estimation (KDE), Temporal Median Filter, etc. [5]. Thus, these methods can be sensitive to noise and small perturbations [1].

In this paper, we present a block-based background subtraction method, RECTGAUSS-Tex, originally proposed in [2]. We have slightly modified the original method to automatically determine the best block size based on the image resolution. In this method, background modeling is done at different scales based on color histograms and the textural content of image blocks. Results show that this method reduces the number of false positives.

### *Background modeling*

The reference image (the first frame of a video sequence) is divided into blocks of size . Originally, the blocks were 4x3, which is not always appropriate, except for 1.33 ratio images. Therefore, we made a change to the method of [2] in order to adapt to different image sizes. Thus, first, the reference image is divided into blocks of size depending on the image ratio. For each block, a color histogram (64 bins for each RGB channel) and the variance of the pixels of the block are calculated. These two statistical measures captures the statistics of the pixels in the blocks and thus of the background. This is the finest scale. blocks are then grouped together and their statistics are merged until a minimum number (user defined) of blocks are obtained. Four blocks at the finest scale gives one block at the next scale, and so on. This gives background image . The background is updated by substituting blocks that are labeled as background during motion detection.

### *Conclusions*

In this paper, the background subtraction method of is applied on the dataset of 3. This method is based on modeling the background with blocks at different scales. First, the background is modeled using blocks that are in turn modeled with a color histogram and the variance of intensities. Then, the Gaussian Mixture background subtraction method is applied to detect significant motion in the finest scale. This method was evaluated in function of performance measures (FNR, Recall, etc.). Results show that our approach reduces **false** positives by filtering noise coming from small motion as it is based on groups of pixels instead of on individual pixels.

# Robust techniques for background subtraction in urban traffic video

***Abstract:***

**Identifying moving objects from a video sequence is a fundamental and critical task in many computer-vision applications. A common approach is to perform background subtraction, which identifies moving objects from the portion of a video frame that differs significantly from a background model. There are many challenges in developing a good background subtraction algorithm. First, it must be robust against changes in illumination. Second, it should avoid detecting non-stationary background objects such as swinging leaves, rain, snow, and shadow cast by moving objects. Finally, its internal background model should react quickly to changes in background such as starting and stopping of vehicles. In this paper, we compare various background sub- traction algorithms for detecting moving vehicles and pedestrians in urban traffic video sequences. We consider approaches varying from simple techniques such as frame differencing and adaptive median filtering, to more sophisticated probabilistic modelling techniques. While complicated techniques often produce superior performance, our experiments show that simple techniques such as adaptive median filtering can produce good results with much lower computational complexity.**

***Introduction***

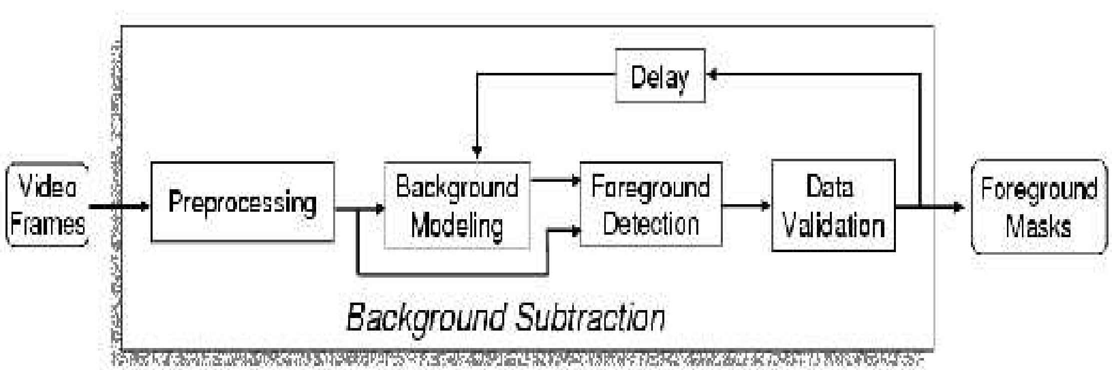
Identifying moving objects from a video sequence is a fundamental and critical task in video surveillance, traffic monitoring and analysis, human detection and tracking, and gesture recognition in human-machine interface.

A common approach to identifying the moving objects is background subtraction, where each video frame is compared against a reference or background model. Pixels in the current frame that deviate significantly from the background are considered to be moving objects. These \foreground" pixels are further processed for object localization and tracking. Since background subtraction is often the first step in many computer vision applications, it is important that the extracted foreground pixels accurately correspond to the moving objects of interest. Even though many background subtraction algorithms have been proposed in the literature, the problem of identifying moving objects in complex environment is still far from being completely solved.

***Background Subtraction Algorithm***

Even though there exist a myriad of background subtraction algorithms in the literature, most of them follow a simple flow diagram shown in Figure 1. The four major steps in a background subtraction algorithm are pre processing, background modeling, foreground detection, and data validation. Pre processing consists of a collection of simple image processing tasks that change the raw input video into a format that can be processed by subsequent steps. Background modeling uses the new video frame to calculate and update a background model. This background model provides a statistical description of the entire background scene. Foreground detection then identifies pixels in the video frame that cannot be adequately explained by the background model, and outputs them as a binary candidate foreground mask. Finally, data validation examines the candidate mask,

Eliminates those pixels that do not correspond to actual moving objects, and outputs the final foreground mask. Domain knowledge and computationally-intensive vision algorithms are often used in data validation. Real-time processing is still feasible as these sophisticated algorithms are applied only on the small number of candidate foreground pixels. Many different approaches have been proposed for each of the four processing steps. We review some of the representative ones in the following subsections.




***Background Subtraction Preprocessing[2]***

In most computer vision systems, simple temporal and/or spatial smoothing are used in the early stage of processing to reduce camera noise. Smoothing can also be used to remove transient environmental noise such as rain and snow captured in outdoor camera. For real-time systems, frame-size and frame-rate reduction are commonly used to reduce the data processing rate. If the camera is moving or multiple cameras are used at different locations, image registration between successive frames or among di_erent cameras is needed before background modeling [1, 2].

### *Background Modelling*

Background modelling is at the heart of any background subtraction algorithm. Much research has been devoted to developing a background model that is robust against environmental changes in the background, but sensitive enough to identify all moving objects of interest. We classify background modelling techniques into two broad categories { non-recursive and recursive. They are described in the following subsections. We focus only on highly-adaptive techniques, and exclude those that require significant resource for initialization. These include schemes described in [13] and [14], which store tens of seconds of video to construct initial background models that are characterized by eigen-images [13] or temporal maximum, minimum, and maximum inter-frame differences of all identified background pixels [14]. For the remainder of this paper, It(x; y) and Bt(x; y) are used to denote the luminance pixel intensity and its background estimate at spatial location (x; y) and time t. The spatial coordinate (x; y) may be dropped if it is not relevant in the description

### *Data Validation*

We define data validation as the process of improving the candidate foreground mask based on information obtained from outside the background model. All the background models in Section 2.2 have three main limitations: first, they ignore any correlation between neigh boring pixels; second, the rate of adaption may not match the moving speed of the foreground objects; and third, non-stationary pixels from moving leaves or shadow cast by moving objects are easily mistaken as true foreground objects.

### *Conclusions*

In this paper, we survey a number of background subtraction algorithms in the literature. We analyze them based on how they differ in pre processing, background modelling, foreground detection, and data validation. More research, however, is needed to improve robustness against environment noise, sudden change of illumination, and to provide a balance between fast adaptation and robust modelling.

### *References*


1.Mittal and D. Huttenlocher, \Scene modeling for wide area surveillancd and image synthesis," in Proceedings

IEEE conference on computer vision and pattern recognition, 2, pp. 160{167, (Hilton Head Isand, SC), June 2000.

2. J. Kang, I. Cohen, and G. Medioni, \Continuous tracking within and across camera streams," in Proceedings IEEE conference on computer vision and pattern recognition, 1, pp. 267{272, (Madison, WI), June 2003.

3. C. Wren, A. Azabayejani, T. Darrel, and A. Pentland, \P_nder: Real-time tracking of the human body," IEEE Transactions on

Pattern Analysis and Machine Intelligence 19, pp. 780{785, July 1997.

4. R. Cutler and L. Davis, \View-based detection," in Proceedings Fourteenth International Conference on Pattern

Recognition, 1, pp. 495{500, (Brisbane, Australia), Aug 1998.

5. A. Elgammal, D. Harwood, and L. Davis, \Non-parametric model for background subtraction," in Proceedings of IEEE ICCV'99 Frame- rate workshop, Sept 1999.

M. Heikkila, M. Pietikainen, A Texture-Based Method for Modeling the Background and Detecting Moving Objects, IEEE Trans: Pattern Analysis and Machine Intelligence, vol. 28, no. 4, pp. 657-662, 2006.

6.Darvish Zadeh Varcheie, P., Sills-Lavoie,M., Bilodeau, G.-A, A Multiscale Region-Based Motion Detection and Background Subtraction Algorithm, Sensors, 10 (2), 2010, pp. 1041-106.

7.McKenna,S., Jabri,S., Duric,Z.,, Rosenfeld,A., Wechsler,H, Tracking Groups of People. Computer Vision and Image Understanding, October 2000, vol. 80, pp. 42-56.

8.Piccardi, M. , "Background subtraction techniques: a review," Systems, Man and Cybernetics, 2004 IEEE International Conference on , 10-13 Oct. 2004, vol. 4, pp. 3099- 3104.

9.Turdu, D., Erdogan, H.,, "Improved post-processing for GMM based adaptive background modeling," Computer and information sciences, 2007. iscis 2007. 22nd international symposium on, Nov. 2007, pp.1-6, 7-9.

[10] S.A. Shafer, and T. Kanade, \Using Shadows in Finding Surface Orientations", CVGIP 22:145-176, 1983.

[11] C. Lin and R. Nevatia, \Building Detection and Description from a Single Intensity Image", CVIU 72:101-121, 1998.

[12] J. Segen, and S. Kumar, \Shadow Gestures: 3D Hand Pose Estimation using a Single Camera", Proceedings of Conference on Computer Vision and Pattern Recognition, 1999.

[13] J-Y. Bouguet, M. Weber, and P. Perona, \What do planar shadows tell about scene geometry?", Proceedings of Conference on Computer Vision and Pattern Recogni-tion, 1999.

[14] A.C. Hurlbert, \The computation of Color", MIT Arti_cial Intelligence Laboratory Technical Report 1154.