Post-print version of the paper by Hanif et al. in WorldCIST'18 2018: AISC, vol 746. pp 491-500
https://doi.org/10.1007/978-3-319-77712-2_46

Performance Analysis of Vehicle Detection Techniques: A Concise Survey

Adnan Hanif[1], Atif Bin Mansoor[2], and Ali Shariq Imran[3]

[1] Department of Avionics Engineering, Air University, Islamabad, Pakistan
[2] School of CSSE, The University of Western Australia, Perth, Australia
[3] Department of Computer Science, NTNU, Gjøvik, Norway
ali.imran@ntnu.no

Abstract. Attention towards Intelligent Transportation System (ITS) has increased manifold especially due to prevailing security situation in the past decade. An integral part of ITS is video-based surveillance systems extracting real-time traffic parameters such as vehicle counting, vehicle classification, vehicle velocity etc. using stationary cameras installed on road sides. In all these systems, robust and reliable detection of vehicles is significantly a critical step. Since, several vehicle detection techniques exist, evaluating these techniques with respect to different environment conditions and application scenarios will give a better choice for actual deployment. The paper presents a concise survey of vehicle detection techniques used in diverse applications of video-based surveillance systems. Moreover, three main detection algorithms; Gaussian Mixture Model (GMM), Histogram of Gradients (HoG), and Adaptive motion Histograms based vehicle detection are implemented and evaluated for performance under varying illumination, traffic density and occlusion conditions. The survey provides a ready-reference for preferred vehicle detection technique under different applications.

Keywords: Vehicle detection · Gaussian Mixture Model · Histogram of Gradients · Performance analysis

1 Introduction

With an ever-increasing vehicular traffic on urban cities roads, the significance of Intelligent Transportation System (ITS) is inevitable. This system is to gather inputs in real time from its traffic sensors which need to be reliable, robust and efficient. An intelligent transportation system for vehicle detection may comprise of different types of sensors including loop detectors, ultrasonic and supersonic sensors, or cameras. In all these sensors vehicle detection using road-side surveillance cameras are most efficient because of their wide area coverage and economical installation procedures [1–3]. Much research has been done during past decades by image processing and computer vision community to assess different traffic parameters from stationary camera video in a real-time. Today, ITS is benefitting most from video-based surveillance systems by extracting and analyzing information useful for traffic planning and security with diverse applications including vehicle counting, vehicle tracking, vehicle trajectory, vehicle classification, vehicle velocity, queue length, license plate recognition, traffic density, traffic lane change etc. [4–7].

However, developing a reliable and efficient video-based vehicle detection system is quite challenging and is a growing field of research. A promising video-based detection system must handle environment dynamics efficiently. It must be adaptive to changes in scene illumination and weather conditions. Jittering camera or noise contamination due to wind are practical issues being faced in vehicle detection. Vehicle shadows under sunlight are also quite challenging to address as long shadows cause occlusion problems and thus incorrect classification in many cases. Similarly, at night time headlights and low illumination poses accurate detection problems. Therefore, detection of moving vehicles under such scenarios is an important yet demanding task.

During past decades many research projects have been done to detect vehicle and extract different traffic parameters from stationary traffic surveillance camera video [8–10]. Early research on vehicle detection techniques from video-based data started in the late 1970s. In 1984, University of Minnesota started a system, called Autoscope which was a wide-area multi-spot video imaging detector [11]. Later on, computer vision, wide-area detection systems developed for advanced vehicular traffic detection and extraction of traffic flow parameters with reduced installation and maintenance cost. A comparative study of vehicle detection between video cameras and loop detectors were carried in 1990's, funded by Minnesota Department of Transportation. The results were favourable for vehicular detection through the wide-area stationary camera as the video-based system was cost effective with several applications in traffic flow analysis and management [12]. Today, almost all applications concerning traffic parameter measurement require robust and reliable detection of a vehicle as a crucial step.

In this review paper, recently published moving vehicle detection techniques from video-based data captured through rectilinear stationary traffic surveillance camera is presented. Our paper primarily focuses on contemporary moving vehicle detection and segmentation techniques, leaving out camera calibration approaches and vehicle tracking methods. While many vehicle detection techniques are available, there has not been any comprehensive survey focusing on their relative performance and detection accuracy under practical scenarios. The paper provides a brief overview of vehicle detection techniques and evaluates the performance of three major vehicle detection techniques under varying illumination, traffic density, and occlusion conditions. It, thus, provides a ready-reference for a preferred choice of vehicle detection technique in actual deployment.

The rest of the paper is organised as follows: In Sect. 2, vehicle detection and segmentation approaches are discussed. The comparative analysis of three major vehicle detection techniques is presented in Sect. 3, and finally, the paper is concluded in Sect. 4.

2 Vehicle Detection and Segmentation Techniques

With advancement in image processing and computer vision techniques, much of the research has been done in the field of moving object's regions of change detection among multiple captured image sequences [13–16]. We categorise the vehicle detection and segmentation techniques based on the approach used in each technique into three methods which are Background Subtraction; Feature Extraction-based and Motion-based. A similar classification was done by [17, 18] but it lacks comprehensive comparative analysis of the methods presented here.

2.1 Background Subtraction Methods

One of the most widely used method for real-time moving vehicle detection and tracking is the Background Subtraction (BS) method. In BS, moving objects are extracted as 'foreground' from each frame by taking an absolute difference between the current frame and the reference frame called 'Background' frame or model. This difference is then thresholded to filter out foreground objects. The essence of the method lies in the accurate estimation of Background model for which both non-adaptive [19] and adaptive [20–22] modelling techniques are available. Since non-adaptive methods suffer from a change in illumination and climate conditions, adaptive modelling is preferred [23].

Early adaptive methods developed by Wren et al. in [24] and Lo et al. in [25] proposed to use moving average and temporal median of the last n frames as the background model, respectively. For I be the intensity of pixel (x, y) at time t and B is the Background model estimated. Then the proposed foreground FG for each frame is computed as: in moving average method as:

$$FG = |I(x, y, t) - B(x, y, t)| > Th$$

where, in the case of moving average method,

$$B(x, y, t) = \frac{1}{n}\sum_{i=0}^{n-1} I(x, y, t - i)$$

and, in the case of temporal median method,

$$B(x, y, t) = \mathrm{median}\{I(x, y, t - i)\}, \quad i \in \{0, \ldots, n - 1\}$$

These methods however, require large memory buffers for its computation and the threshold value Th is non-adaptive and is same for all pixels in frame.

To address this, Ridder et al. [26] used Kalman filter to model each pixel which made their system less susceptible to lighting changes in the scene but poor to handle bimodal backgrounds. A significant work in the field of adaptive background modelling was done by Stauffer and Grimson in [27] by modelling each pixel value x at any time t as a mixture of K Gaussian probability distributions,

$$P(X_t) = \sum_{i=1}^{K} \omega_{i,t} \cdot N(X_t | \mu_{i,t}, \Sigma_{i,t})$$

where,

$$N\left(X_t \mid \mu_{i,t}, \Sigma_{i,t}\right) = \frac{1}{(2\pi)^{D/2}} \frac{1}{\left|\Sigma_{i,t}\right|^{1/2}} \exp\left(-\frac{1}{2}(X_t - \mu_{i,t})^T \Sigma_{i,t}^{-1}\left(X_t - \mu_{i,t}\right)\right)$$

Each pixel in the image scene is classified either as part of the foreground (moving vehicle) or background based on the knowledge of the Gaussian distributions of its pixel model. For μ_i and σ_i be the mean and standard deviation of the K^{th} Gaussian pixel model, then pixel x_t can be classified so as whether,

$$\left(x_t - \mu_{i,t}\right)/\sigma_{i,t} \geq 2.5$$

Later theoretical framework of this approach along with useful corrections is presented in [28].

As an extension to mixture of Gaussian models, authors in [29] presented a combination of background as well as foreground model of each pixel, with background based on Gaussian Mixture Model (GMM) and foreground based on object size, position, velocity, and colour distribution models. In this method, each pixel of the scene can be treated as part of the background, foreground or noise. Yet, velocity model for each foreground objects are to initialise by providing an a priori estimate of object velocity through a learned model of typical traffic direction and speed.

Another technique uses shadows underneath vehicles as the information to detect vehicles [30, 31]. Traffic video normally captured through a camera set up on a low place such as the roadside, sidewalk, etc. is used to determine the size of each vehicle based on the distance between both ends of the front and rear tires. The shadows are segmented for vehicle detection using statistical parameters which automatically update both background subtraction image and binarization threshold.

In [32], frames are subtracted from an adaptive background model which is based on Kalman filtering after dividing the frame into small non-overlapped blocks. A change in gray levels in each block is used for detection of any candidate vehicle part. Then, Principal Component Analysis (PCA) is applied to two histograms of each candidate to produce the low-dimensional feature. Later, a classifier based on support vector machine classifies each block either as part of vehicle or not. Finally, a parallelogram shape represents the vehicle by combining all classifier results.

2.2 Vehicular Feature Based Methods

This method segment moving objects from background image by detecting vehicle's inherent visual features like its colour, edges, contour, texture or body part such as head lights [33–35]. Since the method does not require a vehicle in motion, it can detect stationary vehicle as well. These feature-based methods are less prone to occlusion and perform better even for overlapping vehicles, however, for detection, prior information is required for modelling and therefore, differing feature-based methods result in different computational complexity.

A trainable system for certain class of vehicle detection without using motion, tracking to handcrafted models in unconstrained, cluttered scenes [36] was a breakthrough. The system using a training data of positive and negative example images as input, first transform the images to Haar wavelet representation and then uses a support vector machine classifier to detect in-class and out-of-class static patterns. For vehicle detection in video sequences, the system is augmented with Kalman filtering and detected feature density is modelled and then propagated through time for accurate detection. The system produces appreciable results when applied even to face and people detection.

However, producing a variety of trainable images or models is a mammoth task. An approach in [37] uses computer graphics (CG) model to generate different target vehicles instead of real images for vehicle detection and its classification. The method uses eigenspace technique to obtain local-feature used for subsequent detection and classification. The technique performs well even if parts of the vehicle are occluded, or vehicle translates due to veering out of the lanes. Moreover, it does not require segmentation of vehicle areas from input images.

Another vehicle recognition system proposed by [38] uses image's curvelet transform and standard deviation of curvelet coefficient matrix in different scales for feature extraction. Curvelets having time-frequency localization properties show a high degree of directionality and anisotropy. The approach uses k-nearest neighbour classifier along with different scale information as a feature vector. Recently, [39] used an image descriptor generated from the statistical parameter of the curvelet-transformed sub-bands, for vehicle verification with the hypothesis (candidate) during its detection.

A statistical approach to detection problem proposed by [40] proves robust not only towards partial occlusions but also reduces the computational overhead. For automatic detection, local-features within three significant subregions of image individually generate PCA weight vector and an Independent Component Analysis (ICA) coefficient vector which are used to model the low-frequency components of eigenspace and high-frequency components of the residual space. This improves detection tolerance towards variations in the illumination and vehicle pose.

Another approach [41] for vehicle detection in wide area motion imagery (WAMI) uses Histogram of Gradient (HoG) and Haar descriptors to construct an optimal kernel for the purpose of classification. Here, a cascade of boosting classifier is used to select Haar features from a huge feature set which combined with HoG descriptors, train the final classifier. Results show better classification with fusion of HoG+Haar with Generalized Multiple Kernel Learning (GMKL).

2.3 Motion Based Methods

Optical flow, a computer vision tool, can also be used for detection of objects in motion [42]. The vehicular motion observed from a static camera seems as pixels in the image to be moving. In optical flow, movement of each pixel is calculated by measuring temporal changes of the pixel, and their correlation in an image sequence [43] and the vector field of this motion is referred as Optical flow. Motion based vehicle detection methods trace these flow vectors in 2-D which are produced due to vehicle motion velocity vectors in an image sequence. This approach can even detect independently moving vehicles from the camera. However, optical flow is computationally expensive due to its iterative algorithm and is very susceptible to noise which makes this approach less suitable for real-time video processing without specialised hardware.

Frame differencing is another motion-based detection approach which involves subtracting two consecutive frames by pixel in an image series to obtain moving object pixels and subsequently the moving foreground area by setting a threshold [44]. Variants of the approach with Three-Frame-Differencing [45] and Multi-Frame-Differencing are also used for detection. Although the frame differencing method is very fast and can detect dynamic changes in the background, it cannot cope with noise, abrupt illumination changes, or periodic movement in the background such as trees [46].

In [47] Zhang et al. proposed detection of moving vehicles in the dynamic scenes using two-step algorithm; adaptive background update and motion histogram-based vehicle segmentation. In adaptive background update, lighting changes of the scene evolve the background. In the second step, motion histograms are maintained and updated according to motion information in the scene which later, used to detect moving vehicles in the dynamic scene.

3 Experimental Results

If possible, use standard. In this section, we evaluate most promising detection algorithms, leaving out their slightly improved variants, from each of the three classifications presented in the previous section. The chosen algorithms for comparison are (1) Gaussian Mixture Model foreground detection, (2) Histogram of Gradients feature detection and (3) Detection based on adaptive motion histogram.

The video feed from a stationary camera installed on a highway is first pre-processed to extract frames and then is sent to independent modules implementing the six different algorithms. All algorithms were implemented in OpenCV running on a desktop machine with Intel Core i7 processor and 8 GB RAM. The input data of video feed from a camera is collected over the period of 3 weeks under varying illumination and traffic density conditions. Multiple cases were tested for different scenarios and the output from each module is evaluated in terms of well-known performance metrics of Precision and Recall. Both the metrics are defined as:

- Precision is the ratio of vehicle detected correctly to the total number of detections in the scene i.e.

$$\text{Precision} = \frac{tp}{tp + fp}$$

- Recall is the ratio of the number of vehicle correctly detected to the actual number of vehicle in the scene.

$$\text{Recall} = \frac{tp}{tp + fn}$$

where, tp is true-positive, fp is false-positive and fn is false-negative.

The different scenarios under which the algorithms are tested are:

- Traffic Density: The detection accuracy depends on the density of vehicles on the road inside the coverage area. It can below or high. Since at different times of the day the traffic density vary the detection algorithms performance also varies.
- Illumination Conditions: Lighting affects vision based object detection algorithms. A vehicle detection algorithm which is robust under both bright and dim light condition is preferred in general.
- Occlusion: Vehicles or environmental objects may occlude other vehicles. An algorithm's suitability in real life depends on its performance under occluding conditions.

The first sets of experiments were performed under different traffic densities. The low case refers to less than or equal to 4 vehicles in the frame, and high case refers to more than 8 vehicles in the frame during peak rush hours. Table 1 gives the performance of each algorithm in terms of recall and precision. From Table 1, it is evident that HoG performance is better than the other two even when the traffic density is high. GMM precision and recall suffers under high density as it counts vehicles moving close to each other as one.

Table 1. Impact of traffic density

	Low (< 4 vehicle)		High (> 8 vehicles)	
	Precision(%)	Recall(%)	Precision(%)	Recall(%)
Gaussian Mixture Model	85.71	80.0	82.75	77.41
Histogram of Gradients	92.0	90.19	86.79	88.49
Adaptive Motion Histogram	85.71	88.88	81.35	84.21

Table 2 shows the performance results under different illumination conditions i.e. during day time and night time. It is shown from Table 2 that both precision and recall is less for all the algorithms during afternoon as compared to evening because of strong shadows at day time thereby increasing false positive detections.

Table 2. Impact of illumination condition

	Afternoon		Evening	
	Precision(%)	Recall(%)	Precision(%)	Recall(%)
Gaussian Mixture Model	87.17	77.27	89.47	82.92
Histogram of Gradients	84.50	86.95	88.23	90.90
Adaptive Motion Histogram	89.55	90.85	93.75	92.30

Next, we consider the performance under both occluded and non-occluded case. Table 3 shows the results obtained. It is evident that the performance metrics of each algorithm is higher in the non-occluded case when compared to that of occluded case. In the presence of occlusion, HoG algorithm is more robust than rest as it presents better precision and recall.

Table 3. Impact of occlusion

	Occlusion		No occlusion	
	Precision(%)	Recall(%)	Precision(%)	Recall(%)
Gaussian Mixture Model	81.48	68.75	84.61	75.86
Histogram of Gradients	86.27	88.0	91.67	89.79
Adaptive Motion Histogram	84.44	86.36	90.47	88.37

4 Conclusion

We have presented a survey of categorised vehicle detection methods used for real-time traffic parameters extraction in video-based surveillance systems, one of the integral components of Intelligent Transportation System (ITS). Vehicle detection is a critical yet challenging step, and its performance varies under different practical scenarios and environment conditions. We assessed the performance of three major vehicle detection algorithms under varying illumination, traffic density and occlusion. We observed that Histogram of Gradients (HoG) based detection is more robust than Gaussian Mixture Model (GMM) and Adaptive motion Histograms based detection under high traffic density, and occlusion, making it a preferred candidate in these applications. Our survey gives a better insight of different vehicle detection methods and provides a benchmark for performance improvement in vehicle detection under different applications.

References

1. Fathy, M., Siyal, M.Y.: A window-based image processing technique for quantitative and qualitative analysis of road traffic parameters. IEEE Trans. Veh. Technol. 47(4), 1342–1349 (1998)
2. Cucchiara, R., Piccardi, M., Mello, P.: Image analysis and rule-based reasoning for a traffic monitoring system. IEEE Trans. Intell. Transp. Syst. 1(2), 119–130 (2000)
3. Michalopoulos, P.G.: Vehicle detection through image processing: the autoscope system. IEEE Trans. Veh. Technol. 40(1), 21–29 (1991)
4. Chung-Lin, H., Wen-Chieh, L.: A vision-based vehicle identification system. In: Proceedings of the 17th International Conference on Pattern Recognition, 2004, ICPR 2004, vol. 4, pp. 364–367 (2004)
5. Wei, Z., et al.: Multilevel framework to detect and handle vehicle occlusion. IEEE Trans. Intell. Transp. Syst. 9, 161–174 (2008)
6. Kanhere, N.K., Birchfield, S.T.: Real-time incremental segmentation and tracking of vehicles at low camera angles using stable features. IEEE Trans. Intell. Transp. Syst. 9, 148–160 (2008)
7. Kanhere, N.K.: Vision-Based Detection, Tracking and Classification of Vehicles Using Stable Features With Automatic Camera Calibration, p. 105 (2008)
8. Cao, M., Vu, A., Barth, M.: A novel omni-directional vision sensing technique for traffic surveillance. In: IEEE Intelligent Transportation Systems Conference, pp. 678–683 (2007)
9. Bertozzi, M., Broggi, A., Cellario, M., Fascioli, A., Lombardi, P., Porta, M.: Artifical vision in road vehicles. Proc. IEEE 90(7), 1258–1271 (2002)

10. Bishop, R.: Intelligent vehicle applications worldwide. IEEE Intell. Syst. (2000)
11. Dickmanns, E.: The development of machine vision for road vehicles in the last decade. In: Proceedings of IEEE Intelligent Vehicle Symposium (2002)
12. Anderson, C.A., Michalopoulos, P.G., Jacobson, R.D.: Cost benefit analysis of video-based vehicle detection. In: Proceedings of Vehicle Navigation and Information Systems Conference, pp. 508–515, 30 July–2 August 1995 (1995)
13. Monnet, A., et al.: Background modeling and subtraction of dynamic scenes. In: Presented at the Proceedings of the Ninth IEEE International Conference on Computer Vision, vol. 2 (2003)
14. Monteiro, G., et al.: Robust segmentation for outdoor traffic surveillance. In: 15th IEEE International Conference on Image Processing, 2008, ICIP 2008, pp. 2652–2655 (2008)
15. Spagnolo, P., et al.: Moving object segmentation by background subtraction and temporal analysis. Image Vis. Comput. 24, 411–423 (2006)
16. Weiqiang, W., et al.: Modeling background and segmenting moving objects from compressed video. IEEE Trans. Circ. Syst. Video Technol. 18, 670–681 (2008)
17. Bouwmans, T.: Traditional and recent approaches in background modeling for foreground detection: an overview. Comput. Sci. Rev. (2014)
18. Hadi, R.A., Sulong, G., George, L.E.: Vehicle detection and tracking techniques: a concise review. Sig. Image Process. Int. J. (SIPIJ) 5(1) 2014
19. Diehl, N.: Object-oriented motion estimation and segmentation in image sequences. IEEE Trans. Image Process. 3, 1901–1904 (1990)
20. Kalman, K., Brandt, A.: Moving object recognition using an adaptive background. In: Proceedings of Time-varying Image Processing and Moving Object Recognition, Amsterdam, Netherlands, pp. 289–296 (1990)
21. Odobez, J.M., Bouthemy, P.: Robust multiresolution estimation of parametric motion models. J. Vis. Comm. Image Representation 6, 348–365 (1995)
22. Paragios, N., Tziritas, G.: Adaptive detection and localization of moving objects in image sequences. Sig. Process. Image Commun. 14, 277–296 (1999)
23. Xie, L., Zhu, G., Wang, Y., Xu, H., Zhang, Z.: Robust vehicles extraction in a video-based intelligent transportation systems. In: IEEE 2005 International Conference on Communications, Circuits and Systems, vol. 2, pp. 887–890, May 2005
24. Wren, C., Azarbayejani, A., Darrell, T., Pentland, A.P.: Pfinder: real-time tracking of the human body. IEEE Trans. Pattern Anal. Mach. Intell. 19(7), 780–785 (1997)
25. Lo, B.P.L., Velastin, S.A.: Automatic congestion detection system for underground platforms. In: Proceedings of ISIMP 2001, pp. 158–161, May 2001
26. Ridder, C., Munkelt, O., Kirchner, H.: Adaptive background estimation and foreground detection using kalman-filtering. In: Proceedings of International Conference on recent Advances in Mechatronics, ICRAM 1995, UNESCO Chair on Mechatronics, pp. 193–199 (1995)
27. Stauffer, C., Grimson, W.E.L.: Adaptive background mixture models for real-time tracking. In: Proceedings of IEEE CVPR 1999, pp. 246–252, June 1999
28. Wayne Power, P., Schoonees, J.A.: Understanding background mixture models for foreground segmentation. In: Proceedings of IVCNZ 2002, pp. 267–271, November 2002
29. Magee, D.R.: Tracking multiple vehicles using foreground, background and motion models. Image Vis. Comput. 22, 143–155 (2004)
30. Iwasaki, Y., Itoyama, H.: Real-time vehicle detection using information of shadows underneath vehicles. In: Advances in Computer, Information, and Systems Sciences, and Engineering, pp. 94–98. Springer, Netherlands (2006)

31. Mosabbeb, E.A., Sadegh, M., Fathy, M.: A new approach for vehicle detection in congested traffic scenes based on strong shadow segmentation. In: Advances in Visual Computing Lecture Notes in Computer Science, vol. 4842, pp. 427–436. Springer, Netherlands (2007)
32. Jie, Z., et al.: Moving vehicle detection for automatic traffic monitoring. IEEE Trans. Veh. Technol. 56, 51–59 (2007)
33. Bertozzi, M., Broggi, A., Castelluccio, S.: A real-time oriented system for vehicle detection. J. Syst. Architect. 43(1), 317–325 (1997)
34. Cucchiara, R., Piccardi, M.: Vehicle detection under day and night illumination. In: IIA/SOCO (1999)
35. Guo, D., Fraichard, T., Xie, M., Laugier, C.: Color modeling by spherical influence field in sensing driving environment. In: Proceedings of the IEEE Intelligent Vehicles Symposium, 2000, IV 2000, pp. 249–254 (2000)
36. Papageorgiou, C.P., Poggio, T.: A trainable system for object detection in images and video sequences. Massachusetts Institute of Technology Center for Biological and Computational Learning, vol. 1673 (2000)
37. Yoshida, T., et al.: Vehicle classification system with local-feature based algorithm using CG model images. In: IEICE Transactions on Information and Systems, vol. E85–D, pp. 1745–1752 (2002)
38. Kazemi, F.M., et al.: Vehicle recognition using curvelet transform and thresholding. In: Advances in Computer and Information Sciences and Engineering, pp. 142–146. Springer, Netherlands (2008)
39. Guo, J.-M., Prasetyo, H., Farfoura, M.E., Lee, H.: Vehicle verification using features from curvelet transform and generalized Gaussian distribution modeling. IEEE Trans. Intell. Transp. Syst. 16(4), 1989–1998 (2015)
40. Wang, C.-C.R., Lien, J.-J.J.: Automatic vehicle detection using local features—a statistical approach. IEEE Trans. Intell. Transp. Syst. 9(1), 83–96 (2008)
41. Liang, P., Teodoro, G., Ling, H., Blasch, E., Chen, G., Bai, L.: Multiple kernel learning for vehicle detection in wide area motion imagery. In: 15th International Conference on Information Fusion (FUSION) 2012, pp. 1629–1636, 9–12 July 2012
42. Lucas, B.D., Kanade, T.: An iterative image registration technique with an application to stereo vision. In: Proceedings of Imaging Understanding Workshop, pp. 121–130 (1981)
43. Beauchemin, S.S., Barron, J.L.: The computation of optical flow. ACM Comput. Surv. (CSUR) 27(3), 433–466 (1995)
44. Seki, M., Fujiwara, H., Sumi, K.: A robust background subtraction method for changing background. In: Fifth IEEE Workshop on Applications of Computer Vision, 2000, pp. 207–213 (2000)
45. Zhao, S., et al.: Moving object detecting using gradient information, three-frame-differencing and connectivity testing. In: AI 2006: Advances in Artificial Intelligence, pp. 510–518. Springer, Heidelberg (2006)
46. Buch, N., Velastin, S.A., Orwell, J.: A review of computer vision techniques for the analysis of urban traffic. IEEE Trans. Intell. Transp. Syst. 12(3), 920–939 (2011)
47. Zhang, W., Jonathan Wu, Q.M., bing Yin, H.: Moving vehicles detection based on adaptive motion histogram. Digit. Sig. Process. 20(3), 793–805 (2010)