ISSN: 2456 - 3935
International Journal of Advances in Computer and Electronics Engineering
Volume: 02 Issue: 05, May 2017, pp. 07 – 13

A Review on Video-Based Techniques for Vehicle Detection, Tracking and Behavior Understanding

Ranjeethkumar Chandran
Assistant Professor, (Sr.Gr), Department of Information Technology,
Sri Ramakrishna Engineering College, Coimbatore, India
Email: ranjithkumar.c@gmail.com

Dr. Naveen Raman
Associate professor, Department of Electronics and Communication Engineering,
Info Institute of Engineering, Coimbatore, India
Email: drnaveenraman@gmail.com

Abstract: *The Intelligent Transportation System (ITS) provides services related to different modes of transport and traffic management systems with an integration of traffic control centers. Video-Based investigation for traffic surveillance has been a vital part of ITS. The traffic surveillance in urban environment have become more challenging compared to the highways due to various factors like camera placement, cluttered background, pose variation, object occlusion and illumination changes. This paper provides review on video-based vehicle surveillance for detection, tracking and behavior analysis with systematic description. In this survey we classify the dynamic attributes of vehicle with respect to vehicle motion and appearance characteristics, including velocity, direction of movement, vehicle trajectories on a single camera.*

Keyword: *Behavior understanding; Computer Vision; ITS ; Vehicle Detection; Vehicle Tracking.*

1. INTRODUCTION

The escalation of vehicle in urban areas made traffic surveillance a greater challenge in the medium and large sized cities. The advancements in computer vision, computing and camera technologies have raised the interest in video-based traffic surveillance applications, which has become the key part of intelligent transportation systems (ITS). The existing surveillance system collects traffic flow information that mainly includes traffic parameters and traffic incident detection [1]. The system developed is able to capture vehicles visual appearance and extract more information about them through vehicle detection, tracking, recognition and behavior analysis.

To improve video-based traffic surveillance systems many efforts have been devoted by various researchers, but they still face many challenges and issues in real traffic scenes for an ITS application. The typical scenes include vehicle occlusion, pose variations, all day surveillance and behavior understanding of a vehicle on a single camera network. The variability in vehicle types, size color and pose limits vehicle tracking to specific scenes [40]. An investigation on vehicle detection, tracking and on-road behavior analysis can be found in [32]. A review on various techniques used in video-based traffic surveillance is discussed from a computer vision perspective. These techniques include vehicle detection, tracking and behavior understanding on single camera. This paper also includes improvements, modifications, highlight the advantages and disadvantages.

2. VEHICLE DETECTION

The localization of an image or robust vehicle detection is the first step in video processing. The efficiency & accuracy of vehicle detection is of great importance for vehicle tracking, vehicle movement expression, and behavior understanding and is the basis for subsequent processing [32].The vehicle detection process was divided into appearance based and motion based techniques [1]. The appearance based techniques uses the appearance features like shape, color & texture of the vehicle to detect the vehicle or separate it from the background, whereas the motion based techniques uses the moving characteristic to distinguish vehicles from the stationary background image. A vehicle detection technique with a list of selected publications in each category is shown in Table 1

2.1 Motion-Based Features

Motion detection is an important task in computer vision. In traffic scenes, the most common characteristic of interest is whether a vehicle is “moving” since it is typically only the moving vehicles that are of interest (traffic counts, safety, etc.).Motion detection aims to separate moving foreground objects from the static background in the image. The motion cues are used to distinguish moving vehicles from stationary background, it can be classified into: temporal frame differencing [28] that depends on the last two or three consecutive frames, background subtraction [33], which require frame history to build background model and finally optical flow [24] is based on instantaneous pixel speed on image surface.

TABLE 1 REPRESENTATIVE WORK IN VISION BASED VEHICLE DETECTION.

Techniques	Methods	References
Motion-Based Features	Frame Differencing	[28] [11] [25]
	Background Subtraction	[33] [30]
	1.Median Filter 2. Kalman Filter	[29] [34]
	Single Gaussian pixel distribution	[4] [16]
	Gaussian Mixture Model	[35] [36] [5]
	Optical Flow	[24] [12]
Appearance-Based Features	Feature Based Technique	[37] [14] [15][38] [6] [46] [21] [44]
	1.SIFT 2.HOG 3.Haar-like	
	Part-Based model	[32] [15] [8]

2.1.1 Frame Differencing

The pixel-wise difference is computed between two consecutive frames in temporal frame differencing method. The moving foreground regions are determined using a threshold value [28]. Street-parking vehicles were detected using frame differencing in [11], [13] with noise suppression. Motorcycles were detected in [25]. The use of three consecutive frames improves detection as in [28], where dual inter-frame subtraction are calculated and binarized followed by a bitwise AND to extract the moving target region.

2.1.2 Background Subtraction

Background subtraction methods are the most widely studied and used approach for motion detection. Foreground objects are extracted by calculating the difference by pixel between the current image and a background image [33]. In the simplest case, the background image is constructed by specific known background images, e.g., background averaging method, in which a period of image sequences, are averaged to obtain a background model [30]. However, in real traffic scenes, the background are usually changing; therefore, this kind of method is not suitable for dynamic traffic scenes. Thus, the background is constructed without known background image, which make the following assumptions.

- Background is always the most frequently observed in the image sequence.
- The background pixel has the maximum appearance time at a steady state.

2.1.2.1 Median Filter

In non-recursive median filtering the background is estimated by finding the median value for each pixel from a set of frames stored in a buffer. This technique is based on the assumption that the background pixels will not vary dramatically over a time period. A recursive approximation of the temporal median was proposed in [29]. This technique estimate the median through a simple recursive filter that increases or decreases by one if the input pixel is greater or less than the estimate respectively and it is not changed if it equals. In addition to the high computational complexity of the non-recursive median filtering, its memory requirement is high. In contrast the major strengths of the approximate median filter are its computational efficiency, robustness to noise, and simplicity.

2.1.2.2 Kalman Filter

The Kalman filter [34] is a mathematical power tool that plays an important role in computer graphics. It is also known as linear quadratic estimation. The kalman filter make use of a series of measurements observed over time, containing noise and other inaccuracies, and produces estimates of unknown variables that tend to be more precise than those based on a single measurement alone. The Kalman filter can make full use of the historical information and reduce the search range of the image, to significantly improve system processing speed. The Kalman filter increases the tracking accuracy and stability

2.1.2.3 Single Gaussian Pixel Distribution

Temporal single Gaussian is used to model background recursively, which improve robustness and reduce memory requirement. To achieve more adaptive background model pixels variance was additionally calculated [4]. The model is computed recursively in the form of cumulative running average and standard deviation [16]. Based on the pixel position, each pixel is classified either a background or a foreground pixel. Thus single Gaussian model can be considered as the statistical equivalent of dynamic threshold [16].

This model has limited computational cost; yet it still produces tail effects.

2.1.2.4 Gaussian Mixture Model

Gaussian mixture model (GMM) was introduced by Chris stauffer and W.E.L Grimson in 1999 [35]. It models each pixel as a mixture of two or more Gaussians temporally with online updated data. These distributions are estimated as either a stable background process or short-term foreground process by evaluating its stability. If the distribution of pixels is stable and if above the threshold, then it is termed as background pixel. The speed and adaption rate of the GMM was improved in [36], [7] through extending the standard update equations, by using fixed number of distributions. An improved GMM model using recursive computation was presented in [48], which update GMM parameters continuously. This method is adaptive to light variations and repetitive clutter with higher computational complexity.

2.1.3 Optical Flow

Optical flow is the instantaneous speed of pixels on the image surface, which corresponds to moving objects in 3-D space. The main idea of optical flow is to match pixels between image frames using temporal and gradient information. In [5], dense optical flow was used to separate merged blobs of vehicles. In [24], optical flow was used with 3-D wireframes for vehicle segmentation. The iterative nature of optical flow calculations provides accurate subpixel motion vectors at the expense of added computational time. Yet, optical flow methods are still popular for vehicle detection since these techniques are less susceptible to occlusion issues.

2.2 Appearance-Based Features

The visual information of an object can be categorized into: color, texture, and shape. Prior information is usually employed for modeling when using methods based on these features. The feature extraction method is used to compare the extracted 2-D image features with the true 3-D features in the real world environment. In contrast to motion-based methods, appearance-based methods can detect and recognize stationary objects.

2.2.1 Feature-Based Techniques

The visual appearances of the vehicles are characterized using coded representative feature descriptions. A variety of features have been used in vehicle detection such as local symmetry edge operators. It is sensitive to size and illumination variations, thus a more spatial invariance edge based histogram was used in [41]. These simple features evolve into more general and robust features that allow direct detection and classification of vehicles. Scale Invariant Feature Transformation (SIFT) [12], Histogram of Oriented Gradient (HOG) [19] and Haar-like features [26] are extensively used in vehicle detection literature.

2.2.1.1 Scale Invariant Feature Transformation

In Scale Invariant Feature Transformation (SIFT) [18] the features are detected through a staged filtering approach, which identifies local edge orientation around stable key points in scale space. The generated features are invariant to image scaling, translation, rotation and also it is partially invariant to illumination changes and affine or 3D projection. In addition to the feature vector, the characteristics scale and orientation of every key point is calculated. It can be used to find correspondence of object points in different frames.

2.2.1.2 Histogram of Oriented Gradient

The Histogram of Oriented Gradient (HOG) [19] computes the image gradient directional histogram, which is an integrated presentation of gradient and edge information. It was originally proposed to detect pedestrian, then in [20], it was introduced for vehicle detection by using 3-D model surface instead of 2-D grid of cell to generate 3-D histogram of oriented gradient (3-DHOG). A combination of a latent support vector machine (LSVM) and HOG was used in [9] to combines both local and global features of the vehicle as a deformable object model. Illumination and geometric invariance together with the high computational efficiency are the main advantages of this feature.

2.2.1.3 Haar-Like Features

Haar-like features [26] are formed of sum and differences of rectangles over an image patch to describe the grey-level distribution of adjacent regions. The filters used to extract the features consist of two, three or four that can be at any position and scale. The output of the filter is calculated by adding the pixel values for the grey region and white region separately, and then the difference between the two sums is normalized. A Haar feature was used in [37] to detect vehicles and it was employed to train a cascaded Adaboost classifier. The advantage of this feature are it is sensitive to vertical, horizontal and symmetric structure, which make them well suited for real time application. The disadvantage is that it has a high computational efficiency.

2.2.2 Part-Based Model

Part-based detection models divide an object into a number of smaller parts and model the spatial relationships between these parts, have become popular for vehicle detection recently. Vehicles were separated into front, side, and rear parts to improve detection performance in occlusion and at the edge of the camera FOV [32]. The discriminatively trained deformable part model in [14] is used for robust vehicle detection.

3. VEHICLE TRACKING

Vehicle tracking is used to predict vehicle positions in subsequent frames, match vehicles between adjacent frames, and ultimately obtain the trajectory and location for each frame in the camera FOV of the vehicle. Tracking method gets hold of vehicle trajectory through identifying motion dynamic attributes and characteristics to locate its position in every frame [1].Vehicles tracking can be merged with the detection process or performed separately. The detected vehicles and its correspondence are jointly estimated by updating location iteratively using information obtained from previous frames. In the latter case, vehicle detection is performed in every frame, and data association is used to provide correspondence between vehicles in consecutive frames [32].Current trends in vehicle tracking can be classified into: region-based (shape or contour), and feature-based tracking. A list of selected publications in each category is presented in Table 2.

TABLE 2 REPRESENTATIVE WORK IN VEHICLE TRACKING CATEGORIES.

Techniques	Methods	References
Region-Based Tracking	Shape-Based	Mandellos, et al., [21] Lai, et al., [10]
	Contour-Based	Zhang, et al., [44] Meier, et al., [8]
Feature-Based Tracking	Buch, et al., [22] Bouttefroy, et al., [27]	

3.1 Region-Based Tracking

Tracking based on region detects vehicles silhouette as connected regions within rectangular, oval or any simple geometric shape, which can be characterized by area, coordinates, centroids, edges, contour or intensity histogram etc. Data association between region characteristics within consecutive frame is used to perform tracking.

In [21] shape based tracking with Kalman filtering were used to match simple region. In [10] graph-based region tracking was used for highway vehicles by finding the maximal weight graph. The disadvantages of this technique are computational complexity and its failure in crowded situation. The length and height of the convex hull were used to track vehicle. In [44] the contour of two vehicles was used to resolve occlusion. Vehicle-contour-tracking method was used in [8] to handle visual clutter and partial occlusions.

3.2 Feature-Based Tracking

The feature-based approach is suitable for tracking those targets with small area in the image by compactly representing parts of a vehicle or local areas. The various vehicle features detected are used to perform matching with consecutive frames. The corners and edges were used to represent vehicles in earlier techniques. The combination of corners, edges or interest points with feature descriptors like SIFT [37], HOG [38], [22] and Haar-like [46] are proposed in several techniques for vehicle tracking. Other techniques perform tracking based on color histogram, which is more robust to noise and invariant to vehicle rotation and translation [27].But the main challenge in this technique is to choose appropriate set of features which can effectively represent the moving object (i.e. vehicle).

3.3 Tracking Algorithms

All tracking techniques require prediction and data association process that can be performed using tracking algorithms that include Kalman filter and Particle filter.

3.3.1 Kalman Filter Tracking

Kalman filtering is used to estimate the object position in the new frame assuming that the dynamics of the moving object can be modeled and that the noise effect is stationary with zero mean. The Kalman filter is estimated recursively using the previously estimated states and current measurements to obtain a new state. Projective Kalman filter was combined with mean-shift algorithm in [22] to perform vehicle tracking. To provide accurate estimation of vehicle position, a non-linear projection of the vehicle trajectory is integrated in its observation function. Variable sample rate Kalman filter proposed in [23] track 3D model vehicle on the ground plane. Kalman filter was used in [47] to predict the possible location of the vehicle, and then accurate estimation was achieved by predicted point matching using Gabor wavelet features.

3.3.2 Particle-Filter Tracking

The particle filter is a generalization of the Kalman filter. The basic idea of particle filter is to use a set of random samples with associated weights and estimation based on these samples to represent the posterior probability density. According to Monte Carlo theory, when the number of particles is big enough, the group of particles with associated weight can completely describe a posteriori probability distribution. At this point, the Bayesian estimation of particle filter is optimal [17] is used, which overcomes the constraint of a single Gaussian distribution of Kalman filters. Vehicle contour tracking in [8] is based on particle filter condensation algorithm. Color histogram and edge-based shape features were combined in [39], to improve the efficiency, even with significant color variations, poor lighting, and/or background clutter edges.

4. BEHAVIOR UNDERSTANDING

After dynamic attributes extraction, vehicle behavior understanding will be performed. In this section, we study the behavior understanding techniques on a single camera.

4.1 Behavior Understanding on A Single Camera

Behavior understanding means the classification of time-varying feature data, i.e., matching an unknown test sequence with a group of labeled reference sequences representing typical or learned behaviors [2].Vehicle behavior understanding depends on vehicle trajectories and other dynamic attributes, such as velocity and acceleration. The fundamental issue is that it is difficult to learn the reference behavior sequences from training samples and to devise both training and matching methods for coping effectively with small variations of the feature data within each class of motion pattern. There are two main steps in behavior understanding: First, a dictionary of reference behaviors is constructed, and second, it checks if a match can be found in the dictionary for each observation. The reference behaviors can be applied for two main purposes: explicit event recognition, which means giving a proper semantic interpretations, and anomaly detection, such as traffic event detection (illegal stop vehicles, converse driving, congestion, and crashes) and traffic violation detection (red-light running and illegal lane changing).

4.1.1 Behavior Understanding Based On Trajectory Analysis

Most existing traffic monitoring systems are based on motion trajectory analysis. Trajectory analysis [42] is an important and basic research in behavior analysis and understanding. A motion trajectory is identified by tracking an object from one frame to the next and then linking its positions in consecutive frames. The following describes a common solution framework for vehicle behavior modeling and recognition in traffic monitoring systems using the trajectory-based approach. The spatiotemporal trajectories are created, which describe the motion paths of tracked vehicles. Then, characteristic motion patterns are learned, e.g., clustering these trajectories into prototype curves. Finally, by tracking the position within these prototype curves, motion recognition is tackled. To summarize, learning and analyzing trajectories include three basic steps: trajectory clustering, trajectory modeling, and trajectory retrieval.

4.1.1.1Trajectory Clustering

The key task is to determine an appropriate number of trajectory clusters automatically. Inappropriate setting of the number of trajectory clusters may result in inaccurate trajectory clustering, particularly when the number of trajectories is very large. Stauffer and Grimson [39] learned local trajectory features by vector quantization (VQ) on subimages and learned those features similarities using local co-occurrence measurements to do cluster analysis. Wang et al. [43] utilized spectral clustering to complete trajectory clustering, and help to detect and predict anomalies. Vasquez and Fraichard [45] proposed a rather flexible expectation-maximization algorithm to compute the trajectory similarity, and combined complete-link hierarchical clustering and deterministic annealing pairwise clustering together for trajectory clustering.

4.1.1.2 Trajectory Modeling

Each cluster of trajectories is organized as a trajectory pattern. Trajectory cluster modeling is building a model of trajectories in each cluster according to their statistical distribution, such as a hierarchical Dirichlet process and a Dirichlet process mixture model (DPMM). When a new unknown video pattern is incoming, the time-sensitive DPMM can be performed by using known normal events. The HMM model has been used to represent trajectories and time series successfully.

4.1.1.3 Trajectory Retrieval

In trajectory analysis the user can give a query, such as “find all illegal stop vehicles at 8:00–10:00 in the Southwest road,” and a matching is performed to return all examples in a traffic surveillance database. The posterior probability estimation method is used to match the query trajectory to the corresponding trajectory pattern. The retrieved videos are ranked by the posterior probabilities. There are two common used algorithms to represent and compare trajectories: string matching algorithm and sketch matching algorithm. The string-based method can automatically convert a trajectory to a string and match it using its semantic meanings. Vlachos et al. [18] utilized the longest common subsequence (LCSS) algorithm complete string-based matching trajectories by performing a frame-by-frame analysis directly on objects’ coordinates.

The work in [3] assumed a query by example mechanism according to presented example trajectory and the search system could return a ranked list of most similar items in the data set by a string matching algorithm, whereas the sketch-based method projects a trajectory on a set of basic functions and matches it according to its low-level geometrical features.

5. DISCUSSION ON FUTURE DEVELOPMENT

This section will provide a discussion, analyses and perspectives of challenges and future research directions on video-based traffic surveillance. Most of the work achieved so far deal with highway rather than urban environments. The main technical challenge from the application perspective lies in the camera view and operating condition, which impose many additional limitations [32]. Vehicle surveillance systems undergo various difficulties especially in urban traffic scenarios such as road sections and intersection in which dense traffic, vehicle occlusion, pose and orientation variation and camera placement highly affect their performance.

In road sections vehicles usually travels in a uni-direction in which heavy traffic and congestion may affect vehicle detection due to slow or temporary stopped vehicles. Vehicle pose and orientation with respect to the camera often varies while moving within intersections due to lane change and turn left, right and round. This will vary the appearance and scale of vehicle within consecutive frames affecting tracking and classification dramatically. All of that will increase the complexity of tracking process and affect the real time performance. Nighttime is a dramatic challenge for traffic surveillance, in which headlight and taillights are used to represent the vehicle.

6. CONCLUSION

In this paper, we have provided an extensive review of the state-of-the-art literature addressing computer vision techniques used in video based traffic surveillance and monitoring systems. These systems perform three major operations that are vehicle detection, tracking and behavior understanding. Vehicle detection was divided into two main categories based on vehicle representation, namely, techniques based on motion cues and techniques that employ appearance features. Both techniques can be used to isolate vehicles from the background scene with different computational complexity and detection accuracy. Vehicle tracking was categorized into region and feature based tracking with a discussion on motion and parameter estimation schemes employed like Kalman and Particle filtering.

We also provide a detailed summarize on vehicle behavior understanding on a single camera using trajectory information. We believe that, this paper provides a rich bibliography content regarding vehicles surveillance systems, which can provide valuable insight into this important research area and encourage new research.

REFERENCES

[1] B. Tian, B.T. Morris, M. Tang, Y. Liu, Y. Yao, C. Gou, D.Shen, and S. Tang, (2015) "Hierarchical and networked vehicle surveillance in ITS: A survey," *IEEE Transactions on Intelligent Transportation Systems*, vol. 16, no. 2, pp. 557-580.

[2] Bobick and J. Davis (2001), "The recognition of human Movement using temporal templates," *IEEE Trans. Pattern Anal. Machine Intelligence*. vol. 23, no. 3, pp. 257–267.

[3] Bashir, A. Khokhar, and D. Schonfeld (2007), "Real-time Motion trajectory based indexing and retrieval of video sequences," *IEEE Transactions Multimedia*, vol. 9, no. 1, pp. 58– 65

[4] C.R. Wren, A. Azarbayejani, T. Darrell, and A.P. Pentland (1997), "Pfinder :Real-time tracking of the human body," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 19, no. 7, pp. 780-785.

[5] C.-L. Huang and W.-C. Liao (2004), "A vision-based vehicle Identification system," *in Proc. Int. Conf. Pattern Recognition*, vol. 4, pp. 364–367.

[6] C. Szegedy, A. Toshev, and D. Erhan (2013), "Deep neural Networks for object detection," in *Proc. Advance. Neural Information Processing Syst*ems, pp. 2553–2561.

[7] S. Kalaivani, Rahul Singh Thakur, Dharmendra (2017), "Modified Hidden Markov Model for Speaker Identification System" *International Journal of Advances in Computer and Electronics Engineering*, Vol .2. no.3, pp.1-7

[8] E.B. Meier and F. Ade (1999), "Tracking cars in range images using the condensation algorithm," in *Proc. IEEE International Conference on Intelligent Transportation Systems*, pp.129-134.

[9] H.T. Niknejad, A. Takeuchi, S. Mita, and D. McAllester (2012), "On road multivehicle tracking using deformable object model and particle filter with improved likelihood estimation," *IEEETransactions on Intelligent Transportation Systems*, vol. 13, no. 2, pp. 748-758.

[10] J.C. Lai, S.S. Huang, and C.C. Tseng (2010), "Image-based Vehicle tracking and classification on the highway," in *International Conference on Green Circuits and Systems* (ICGCS), pp. 666-670.

[11] K. Park, D. Lee, and Y. Park (2007), "Video-based detection of street parking violation*", in Proc. International Conference on Image Processing, Computer Vision, and Pattern Recognition (IPCV)*, pp. 152-156.

[12] K.M.A. Yousef, M. Al-Tabanjah, E. Hudaib, and M. Ikrai (2015), "SIFT based automatic number plate recognition," *in proc. IEEE 6th International Conference on Information and Communication Systems* (ICICS), pp. 124-129.

[13] Kalaiselvi Kandasamy, Renuga Perumal (2017), "Electric Grid and Vehicle Integration using ANFIS Controller in Smart Grid Context", *International Journal of Advances in Computer and Electronics Engineering*, Vol .2. no.4, pp.14-19.

[14] L. Lin, T. Wu, J. Porway, and Z. Xu (2009), "A stochastic Graph grammar for compositional object representation and recognition," *Pattern Recognition*, vol. 42, no. 7, pp. 1297-1307

[15] Lai and N. H. C. Yung (1998), "A fast and accurate Scoreboard algorithm for estimating stationary backgrounds in an image sequence," in *Proc. IEEE Int. Symp. Circuits Systems*, vol. 4, pp. 241–244.

[16] Morris, and M. Trivedi (2006), "Improved vehicle classification in Long traffic video by cooperating tracker and classifier modules," *IEEE International Conference on Video and Signal Based Surveillance* (AVSS), pp. 9-11.

[17] M. S. Arulampalam, S. Maskell, N. Gordon, and T. Clapp (2002), "A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking*," IEEE Trans. Signal Process*., vol. 50, no 2, pp. 174–188.

[18] M. Vlachos, G. Kollios, and D. Gunopulos (2002), "Discovering similar multidimensional trajectories," in Proceedings *Int. Conf. Data Eng*., pp. 673–684.

[19] N. Dalal, and B. Triggs (2005), "Histograms of oriented gradients for human detection," in proc. *IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, vol. 1, pp. 886-893.

[20] N. Buch, J. Orwell, and S.A. Velastin (2001), "3D extended Histogram of oriented gradients (3DHOG) for classification of

ISSN: 2456 - 3935

International Journal of Advances in Computer and Electronics Engineering
Volume: 02 Issue: 05, May 2017, pp. 07 – 13

road users in urban scenes," in *Proc. of the British Machine Conference*, pp. 15-1.

[21] N.A. Mandellos, I. Keramitsoglou, and C.T. Kiranoudis (2011), "A background subtraction algorithm for detecting and tracking vehicles*," Expert Systems with Applications*, vol. 38, no. 3, pp. 1619-1631.

[22] N. Buch, J. Orwell, and S.A. Velastin, "3D extended histogram of oriented gradients (3DHOG) for classification of road users in urban scenes," in *Proc. of the British Machine Conference*, pp. 15-1.

[23] N. Buch, F. Yin, J. Orwell, D. Makris, and S.A. Velastin (2009),"Urban vehicle tracking using a combined 3D model detector and classifier," in *Knowledge-Based and Intelligent Information and Engineering Systems*, pp. 169- 176.

[24] Ottlik and H.-H. Nagel (2008), "Initialization of model- based vehicle tracking in video sequences of inner-city intersections," *International journal of Computer Vision.*, vol. 80, no. 2, pp. 211–225.

[25] P.V. Nguyen, and H.B. Le (2008), "A multi-modal particle filter based motorcycle tracking system", *In PRICAI 2008: Trend in Artificial Intelligence*, pp. 819-828.

[26] P. Viola, and M. Jones (2001), "Rapid object detection using a boosted cascade of simple features," *in proc. of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, vol. 1, pp. I-511.

[27] P.L.M. Bouttefroy, A. Bouzerdoum, S.L. Phung, and A. Beghdadi (2009), "Vehicle tracking using projective particle filter," in *IEEE 6th International Conference on Advanced Video and Signal Based Surveillance*, pp. 7-12.

[28] Q.L. Li, and J.F. He (2011), "Vehicles detection based on three frame difference method and cross-entropy threshold method," *Computer Engineering*, vol. 37, no. 4, pp. 172-174.

[29] R. Manikandan, and R. Ramakrishnan (2013), "Video object Extraction by using background subtraction techniques for sports applications," *Digital Image Processing*, vol. 5, no. 9, pp. 435-440.

[30] R. Cucchiara, C. Grana, M. Piccardi, and A. Prati (2003), "Detecting moving objects, ghosts, and shadows in video streams," *IEEETransactions on Pattern Analysis and Machine Intelligence*, vol. 25, no. 10, pp. 1337-1342.

[31] R. Hamid et al (2010)., "Player localization using multiple Static cameras for sports visualization," *in Proc. IEEE Conf. Computer Vision Pattern Recognition*. pp. 731– 738.

[32] S. Sivaraman, and M.M. Trivedi (2013), "Looking at vehicles on the road: A survey of vision-based vehicle detection, tracking, and behavior analysis," *IEEE Transactions on Intelligent Transportation Systems*, vol. 14, no. 4, pp. 1773-1795.

[33] S. Gupte, O. Masoud, R. F. K. Martin, and N. P. Papanikolopoulos (2002), "Detection and classification of vehicles," *IEEE Transactions on Intelleligent. Transportation Systems*, vol. 3, no. 1, pp. 37–47.

[34] S. Messelodi, C. M. Modena, and M. Zanin (2005), "A Computer vision system for the detection and classification of vehicles at urban road intersections," Pattern Anal. Appl., vol. 8, no.1/2, pp. 17–31.

[35] Stauffer, and W.E.L. Grimson (1999), "Adaptive background Mixture models for real-time tracking," *IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, vol. 2.

[36] S.C. Sen-Ching, and C. Kamath (2004), "Robust techniques for background subtraction in urban traffic video," *International Society for Optics and Photonics in Electronic Imaging*, pp. 881-892.

[37] S.M. Elkerdawi, R. Sayed, and M. ElHelw (2014), "Real-time Vehicle detection and tracking using Haar-like features and compressive tracking," in *1st Iberian Robotics Conference* pp. 381-390.

[38] S. Agarwal, A. Awan, and D. Roth (2004), "Learning to detect Objects in images via a sparse, part-based representation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 26, no. 11, pp. 1475-1490.

[39] Stauffer and W. E. L. Grimson (2000), "Learning patterns of activity using real-time tracking," *IEEE Trans. Pattern Anal. Mach.Intell.*, vol. 22, no. 8, pp. 747–757.

[40] Tian, Y. Li, B. Li, and D. Wen (2014), "Rear-view vehicle Detection and tracking by combining multiple parts for Complex Urban surveillance," *IEEE Transactions on Intelligent transportation*, vol. 15, no. 2, pp. 597-606.

[41] T. Gao, Z.G. Liu, W.C. Gao, and J. Zhang (2009), "Moving Vehicle tracking based on SIFT active particle choosing," in *Advances in Neuro-Information Processing*, pp. 695-702.

[42] T. Morris and M. M. Trivedi (2008), "A survey of vision-based trajectory learning and analysis for surveillance," *IEEE Transactions on Circuits Systems. Video Technol*., vol. 18, no. 8, pp. 1114–1127.

[43] Vasquez and T. Fraichard (2004), "Motion prediction for moving objects: A statistical approach," in *Proc. IEEE Int. Conf. Robot. Automation*, vol. 4, pp. 3931–3936.

[44] W. Zhang, Q.J. Wu, X. Yang, and X. Fang (2008), "Multilevel framework to detect and handle vehicle occlusion," *IEEE Transactions on Intelligent Transportation Systems*, vol. 9, no. 1, pp. 161-174

[45] X. Wang, K. Tieu, and E. Grimson (2006), "Learning Semantic Scene Models by Trajectory Analysis", Berlin, Germany: *Springer-Verlag*, pp. 110–123.

[46] Y. Freund (1995), "Boosting a weak learning algorithm by majority," *Inf. Comput.*, vol. 121, no. 2, pp. 256–285.

[47] Y. Du, and F. Yuan (2009), "Real-time vehicle tracking by Kalman filtering and Gabor decomposition," in *1st International Conference on Information Science and Engineering* (ICISE), pp. 1386-1390.

[48] Z. Zivkovic, and F. van der Heijden (2006), "Efficient Adaptive density estimation per image pixel for the task of background subtraction," *Pattern recognition letters*, vol. 27, no. 7, pp.773-780.

Authors Biography

Ranjeethkumar Chandran, is an Assistant Professor, in Sri Ramakrishna Engineering College, Coimbatore. He completed his B. Tech in IT at Dr. Mahalingam College of Engineering and Technology. He completed his M.E in CSE at Sri Krishna College of Engineering and Technology. His research interests are Image Processing and Networks.

Dr. Naveen Raman, is an Associate Professor, in Info Institute of Engineering, Coimbatore. He completed his B.E in EEE at CSI College of Engineering. He completed his M.E in VLSI at KSR College. Currently 4 scholars are pursuing research in Anna University, Chennai under his guidance. His research interests are Image Processing, Low power VLSI.