regions which are static region (the roadway) and dynamic region (moving vehicles). The static background is then deleted to the locate moving objects in each frame. The result zone leaves only vehicles and some of the details as moving objects in sequential images which are changing frame to frame. A combination of forward and backward image differencing method and also Sobel edge detector has been used in this work. According to this method, the three sequential frames are chosen and the middle one should be compared to its previous and the next frames. Consequently, extracted edges of each of the frame detected by Canny edge detection achieved from previous section are used here. Then the differences of the frames can be obtained just by subtracting each two sequential pair of generated binary images, as in equation 1:

BinaryImage (Canny (Fn-1) ∩ Canny (Fn)) – **BinaryImage** (Canny (Fn) ∩ Canny (Fn+1)) …………..(1)
Where Fn-1 is previous frame, Fn is current frame and Fn+1 is the next frame. This process continues to the last three sequential video frames.

2.2.1 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 such that the background pixels will not vary dramatically over a time period. 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 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.

2.2.2 Kalman Filter: The Kalman filter 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 series of measurements observed over time, containing noise and other inaccuracies, and produces estimates of unknown variables that tend to be more precise and than those based on a single measurement alone. The Kalman filter can make full use of the historical information and reduce the whole search range of the image, to significantly improve system processing speed. The Kalman filter increases the tracking accuracy and stability

2.2.3 Single Gaussian Pixel Distribution Temporal single Gaussian is used to model back: It 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].

2.3 VIDEO PROCESSING: Video processing is a subclass of Digital Signal Processing techniques where the input and output signals are video streams. In computers, one of the best important ways to reach video analysis goals is using image processing methods in each video frame. Here motions are simply realized by comparing sequential frames. Video processing includes prefiltering, which can cause contrast changes and noise elimination along with video frames pixel size conversions and Highlights particular areas of videos, deleting unsuitable lighting effects, just eliminating camera motions and removing edge artifacts are performable using video processing methods. Open Cv library of python is equipped with many functions that helps us to manipulate videos and images. Open CV Python makes use of Numpy technique, which is a library for numerical operations with a MATLAB style syntax. All the Open CV array structures are converted from one to another Numpy arrays.

2.4 RGB TO GRAYSCALE CONVERSION:
The sequence of captured video frames should be transformed from RGB color mode to a 0 to 255 gray levels. When converting an RGB image to a grayscale mode, the RGB values for each pixel must be taken, and a single value reflecting the brightness percentage of that pixel should be prepared as an output data.

2.5 DETECTION ZONE: As an observation (detection) zone, a region must be defined to display moving vehicle's edges in a bounding box at the time that the vehicle enters it. This zone is in middle of the screen and covers about 1/3 of its height and 3/5 of its width (considering minimum and maximum available size of detectable passing vehicles in pixels). This area which contains the most traffic can embed both small and long vehicles and the main goal of defining it is to avoid perspective challenges and thewrong type counts. Based on the proposed method in background subtraction level, a vehicle is detected in three sequential frames. When a moving vehicle is detected, the bounding box whelming vehicle borders in binary image is drawn.

2.6 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 behind optical flow is to match pixels between image frames using temporal and gradient information. The dense optical flow was used to separate merged blobs of vehicles., 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, the optical flow methods are still popular for vehicle detection since these techniques are less susceptible to occlusion issues.

2.7 APPEARANCE-BASED FEATURES: The visual information of an object can be categorized into: color, texture, and shape. Prior informations are 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.

2.7.1 Feature-Based Techniques: The visual appearances of the vehicles are characterized using the coded representative feature descriptions. A variety of features have been used in vehicle detection such as the local symmetry edge operators. It is sensitive to size and illumination variations. These simple features evolve into more general and robust features that allow direct detection and classification of vehicles. Scale Invariant Feature Transformation (SIFT) , Histogram of Oriented Gradient (HOG) and Haar like features are extensively used in vehicle detection literature.

2.7.2 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 the correspondence of object points in different frames.

2.7.3 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-Dgrid 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.
1.7.4 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.

2.8. 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.

2.8.1 Region-Based Tracking: Tracking based on region detects vehicles is 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 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.

2.8.2 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 , HOG and Haar 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 the appropriate set of features which can effectively represent the moving object (i.e. vehicle).

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., [38] Meier, et al., [8]
Feature-Based Tracking	Buch, et al., [22] Bouttefroy, et al., [27]	

2.8.3 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.

a) 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.

b) 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 inorder to represent the posterior probability density. According to Monte Carlo theory, when the number of particles is big enough, then 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 , to improve the efficiency, even with significant color variations, poor lighting, and/or background clutter edges.

2.9 COUNTING AND CLASSIFICATION FUNCTIONS: Vehicle counters are used in computing capacity, establishing structural design criteria and computing expected roadway user revenue [10]. Typically in the proposed technique vehicles are classified as four common types:

- Type1: bicycles, motorcycles
- Type2: motorcars
- Type3: pickups, minibuses
- Type4: buses, trucks, trailers

It is necessary to have the width and length of each vehicle's bounding boxes in pixels range to diagnose that the passing vehicles belongs to which of the mentioned types. The area of each bounding boxes shows which type should be allocated for the vehicle. Each vehicle type can be shown by a special type of rectangle color. Type 1 has been represented by red, and Type2, Type 3 and Type 4 have been characterized by green, blue and yellow rectangles, respectively.

In counting step, four isolated counters used for each vehicle type and also a total counter is needed to store the sum value of them. All counters should count just the vehicles which are passing in specific direction. So if a vehicle stops, turns or moves in wrong direction in the detection zone such that it should not be counted. In this technique, counting is according to the total number of moving vehicles detected in the detection zone and classified in one of mentioned groups.

Total passed vehicles, which will be shown in yellow, help us to analyze traffic flow in a period of time. Also by then calculating the bounding boxes height and width in pixels, vehicle types can be distinguished and counted by related counters. Furthermore, in both counted vehicles, edges will be covered with green rectangles, which shows that they belong to Type 2 (even the green numbers inside bounding boxes confirm this result).

3. 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 the vehicle representation, namely, techniques based on motion cues and techniques that employ appearance features. Both techniques can be used to isolate vehicles from 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 in sight into this important research area and encourage new research. Python is very good library like numpy, matplotlib, scipy, which can help to count traffic, classify the traffic and save the time of engineer.

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 Systems, 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 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..