Huijie et al. [59] studied a number of video based surveillance systems and found that the presence of shadow and illumination in a video frame or image can significantly affect the vehicle detection and tracking. In addition, they stated that the presence of occlusion is one of the most vital issues to be dealt with efficiently.

Page et al. [60] developed moving vehicle detection and tracking system using Gotcha radar systems. Authors applied the feedback information of the tracking component to deal with detection issues and allied false alarm problems. The authors derived a mathematical model to process multichannel SAR data so as to alleviate the combined influences of moving target defocus and clutter caused interference. The algorithm applies MRP mechanism dynamically in a STAP model so as to focus up moving vehicles and optimize signal to clutter ratios for better performance.

Jyothirmai et al. [61] proposed a video based surveillance system for security purpose. They applied background subtraction based moving vehicle detection and tracking algorithm. In addition, they introduced various threshold levels to identify moving object of certain sizes.

Li et al. [62] developed an adaptive background subtraction model in combination with a virtual detector and blob tracking method for vision based vehicle detection and tracking.

Bhaskaret al. [63] addressed the vehicle detection and tracking in traffic video data. Authors applied Gaussian Mixture Model (GMM) and blob detection approach to perform vehicle detection and tracking.

Brahme et al. [64] applied blob analysis technique to perform vehicle counting to be applied for traffic surveillance. Authors applied moving object segmentation and blob analysis to perform moving vehicle detection and tracking. At first, they performed blob
analysis, based on which they extracted significant features. Based on blob analysis, authors performed vehicle speed estimation.

Cho et al., [65] developed visual feature extraction model for object detection and tracking system which they were later applied for vehicle, pedestrians, and bicyclists detection. The retrieved visual recognition information was applied to enhance object detection and data association model that eventually enabled movement classification.

Xu et al., [66] examined various approaches and techniques for vehicle detection and tracking. Author stated that no doubt a number of approaches have been developed; however, there is the need to develop robust and more effective vehicle detection and tracking model especially in heavy traffic conditions.

Lin et al., [67] applied color background feature to perform multiple-vehicle detection and tracking (MVDT). Authors exploited the inter-relationship between the moving objects and relative trajectories to perform tracking.

Demars et al. [68] developed moving vehicle detection and tracking in full motion video (FMV) using aerial imaging systems. Researchers emphasized on enhancing the probability of detection and tracking even in cluttered urban environments. To achieve this, they suppressed false alarms by amalgamating the detection outputs and related features from varied spectral bands. Authors used GMM model for background pixel detection which was used to identify vehicle (as foreground). Authors amalgamated the features extracted from the individual spectral band so as to construct multi-spectral target region. The detected target candidates were connected to the targets from a tracking database by means of matching associated features from the scale-invariant feature transform (SIFT).

Aytekin et al., [69] explored the significance of monochrome images retrieved through a single camera to perform vehicle detection and tracking. They emphasized on
vehicle detection and tracking in daylight conditions, where the data is obtained from inside a vehicle. In implementation, they employed vehicle shadow clues and associated edge information to retrieve fast detection. In addition, they incorporated lane detection model to alleviate the issue of false detections (caused due to background interferences). Considering that the road-lanes are detected, the presence of vehicle inside the road area is assumed by considering “shadow” as a cue. Authors have verified hypothesized vehicle locations using vertical edges. With the detected features (from vehicle region), Kalman filter was used to perform tracking.

Li et al. [70] developed MVDT comprising three functional phases, road detection, vehicle detection, and vehicle tracking. To perform road detection, they applied a plane-fitting feature, followed by the use of segmented blob and snakes blob features and artificial neural network (ANN) to detect vehicle on road.

Chen et al. [71] used headlights and taillights feature and the techniques like image segmentation and pattern analysis to perform vehicle detection and tracking. At first, they applied automatic multilevel thresholding approach for vehicle region segmentation. The extracted bright component (here headlight of vehicle) were processed to perform vehicles tracking by locating the spatial and temporal features of vehicle light patterns.

Lin et al. [72] developed vehicle detection and tracking system functional under occlusion condition to enable an efficient driver assistant system (DAS). To enable an intelligent tracking model, they classified the targets into three classes. They applied edge feature localization method in conjunction with the template matching to track the normal state. Further, they solved the tracking window drifting issue by the template update approach with target feature comparability.

Lu et al. [73] to provide vehicle detection in daylight traffic developed SEAP (Simple but Efficient After Process) to verify the detection outcomes in an accurate manner which was then processed with Adaboost detector to perform car detection in
dense traffic. Further, authors developed 4-states tracking algorithm using Kalman linear filter to perform vehicle (here car) tracking. Their applied 4-states tracking algorithm solved the issue of false positive issues in dense traffic condition. To achieve this, they applied FSM (Finite State Machine) concept to perform tracking.

Liu et al. [74] developed monocular vision based rear vehicle detection and tracking system to be used for Lane Change Assistance (LCA) purposes. The prime novelty of this approach was that it does not require road-lane boundary information. They extracted ROI using the vehicle shadow information. Applying vehicle regions in ROI they extracted key features like vehicle region symmetry, edge and shadow underneath vehicles to perform tracking.

Nateghinia et al. [75] developed video-based vehicle detection and tracking system based on a combined background estimation and dynamic texture modeling. After extracting vehicles from the video frames, a point tracking method has been used to predict vehicles central points in the next frames. They have applied weighted recursive least square scheme for point tracking purpose. Moreover, to solve the occlusion of two or more vehicles problem, fast normalized cross correlation algorithm has been used as a template matching method.

Kowsari et al. [76] developed multilayer, real-time vehicle detection and tracking system where they applied stereo vision, optical flow technique and multi-view AdaBoost detectors. Applying a ground plane measures retrieved from stereo information, they generated certain hypotheses and used trained AdaBoost classifiers other than fast disparity histogramming, for Hypothesis Verification (HV) purposes. To perform tracking, authors applied Kalman filter and motion vectors from optical flow that strengthened their tracking model.
Fu et al., [77] presented vehicle detection and tracking system using SVM-based particle filtering model that incorporates SVM score in conjunction with sampling weights. Here, the sampling weights were applied to form a probability distribution of samples by the SVM score.

Kim et al. [78] applied vision sensor to derive DAS model to be used for collision warning and avoidance decision process. The prime contribution of their work was that it could perform vehicle detection and tracking regardless of the light and road conditions and even at any distance. To achieve this, they exploited the efficacy of sonar and vision sensor systems. At first, they developed a model for light condition estimation where they observing multiple images. For day time detection, they extracted shadow region characterised by the boundary in between a vehicle and the road, which was further verified by means of other vehicle features, like symmetry rate, vertical edge, and lane information. In fact, to perform day time tracking they applied online template matching approach employing the mean image formed by numerous consecutive detection outcomes. On the other hand, for night time detection they extracted bright regions caused due to active headlights, taillights etc.

Li et al. [79] developed a vision-based approach to perform forward vehicle detection and tracking. At first, they applied histogram method to perform shadow segmentation beneath vehicle region. They generated the initial candidates by joining horizontal as well as vertical (shadow) edge features. Further they verified the obtained initial candidate features by means of a vehicle classifier model functional on the basis of histogram of gradient and SVM. Authors applied Kalman filters to perform vehicle tracking.

Cui et al. [80] developed a robust multilane detection and tracking method where they used in-vehicle mono-camera and a forward-looking LIDAR technique. Their approach could address the key issues in real world scenarios, especially in urban driving situations. They applied steerable filters to perform lane feature detection. In addition, they applied LIDAR-based image drivable space segmentation to identify lane marking
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point’s validations. Furthermore, the Random Sample Consensus approach was used for robust lane model fitting. Thus, the detected lanes initialize particle filters to perform vehicle tracking, without demanding the ego-motion information.

Lee et al., [81] applied the concept of tracking feature points to perform real-time vehicle detection and lane change detection. Authors stated their approach as switch-independent which was not depending on the illumination conditions. Their approach comprised three phases, corner feature point extraction, (vehicle) feature point tracking and lane-change event detection and violating vehicle detection. Authors developed a robust corner feature extraction model, where the salient points were chosen amidst the corner points to perform vehicle registration and tracking. Furthermore, they applied normalised cross-correlation method to perform registered feature point tracking. Ultimately, illegal lane-change events were determined by the information retrieved from the tracked corners without performing grouping (for segmentation). They assessed their model in terms of accuracy where it was found satisfactory.

Danescu et al. [82] introduced an approach for pitch detection on the basis of fusion of the two stereovision-based cues, a novel method for particle measurement and weighting by means of multiple lane delimiting cues extracted by gray scale and stereo data processing.

Eng et al., [83] defined the statistical characteristics of the background pixels and detected foreground objects in the current frame by means of subtracting the current frame with respect to the background color model and background edge model. The consideration of color and edge features made their approach robust enough to perform accurate detection.

Alefs et al. [84] considered statistical data retrieved from the bidirectional traffic to perform vehicle tracking. Further using the continuous data retrieval, they estimated the vehicle speed. At first, they applied block based variant of the Adaboost detection...
model with edge orientation histograms to perform detection. In their model, they applied extended Lucas Kanade template matching model.

Wang et al. [85] performed in depth exploration or review of vehicle detection and tracking approaches functional on the basis of stationary video. Authors emphasized on systems where the rectilinear stationary camera is placed on roadside rather than vehicle-mounted.

Yao et al. [86] presented a fast and robust road curb detection algorithm using 3D lidar data and Integral Laser Points (ILP) features. Range and intensity data of the 3D lidar is decomposed into elevation data and data projected on the ground plane. First, left and right road curbs are detected for each scan line using the ground projected range and intensity data and line segment features. Then, curb points of each scan line are determined using elevation data. The ILP features are proposed to speed up the both detection procedures. Finally, parabola model and RANSAC algorithm is used to fit the left and right curb points and generate vehicle controlling parameters.

Choi et al. [87] proposed multiple vehicles detection using quad-tree segmentation and in later stage applied SIFT algorithm to perform tracking.

Afrin et al. [88] developed a system that facilitates autonomous speed breaker data collection, dynamic speed breaker detection and warning generation for the on-road drivers. Their system incorporates real-time tracking of driver, vehicle and timing information for speed breaker rule violations.

Li et al. [89] developed a video-based traffic information retrieval model where they tracked and classified passing vehicle under crowded traffic conditions. At first, they obtained the type and speed of each passing vehicles. Authors applied adaptive background subtraction model to perform vehicle detection. In later stage, executed shadow removal and road region detection to enhance efficiency. Furthermore, to
minimize the classification errors, the space ratio of the blob and data fusion were used to reduce the classification errors caused by vehicle occlusions.

Kiratiratanapruk et al. [90] presented a video based surveillance system for real-time purposes where they applied their vehicle detection and tracking model for traffic parameters estimation such as vehicle velocity and vehicle counts. They applied background detection model based on border information so as to distinguish moving foreground objects from the background. Benefit of edge was found advantageous as it enabled proposed model resilient to the lighting variations in outdoor atmospheres. In tracking process, optical flow Lucas-Kanade (Pyramid) was applied to track every segmented object.

Kiratiratanapruk et al., [91] modeled a background subtraction model using edge information for extracting foreground moving objects. The benefit of using border information to replica the background was its robustness to the lighting variation and low computing resources than intensity based background model. It enabled their approach suitable for real-time application.

Lu et al., [92] proposed 4-states tracking algorithm on the basis of Kalman linear filter. In case of highly crowded scenario where significantly higher false positives and false negatives result emerges. However, 4-states tracking algorithm alleviates it and resolved it though Finite State Machine model to perform tracking.

Lin et al., [93] developed image tracker that contains three parts, border detection, image tracking and a traffic monitoring unit. The border-detection model is a unique designed circuit board that characterizes speedy CCD image processing and feature extraction. With the frame rate of 60 Hz they performed border detection of an image with resolution of 320×240 pixels. Adoptive active contour models and Kalman filtering methods were developed to perform tracking of the multi-lane moving vehicles.
Datondji et al. [94] presented a survey of vehicle detection and tracking in crossroads situations. As regards junction monitoring, they differentiated and compared roadside (pole-mounted, fixed) as well as in-vehicle (mobile) systems. After that with particular concentration to omnidirectional setups, they focused on camera-based roadside monitoring systems.

Jiang et al. [95] emphasized on alleviating the issues of spatial segmentation during vehicle detection. They applied well known concept of "Temporary vehicle", "confirmed vehicle" based on which they further derived a Fuzzy rule for vehicle identification under occlusion.

Jiang et al., [96] performed motion segmentation combined with background subtraction with motion edge detection for vehicle detection, which was followed by tracking using certain vehicle features. To identify the momentarily missed vehicles during occlusion they applied the approach of "confirmed vehicle" and "temporary vehicle".

Yang et al., [97] exploited windshield model matching approach for vehicle detection that enabled it to function even under occlusion condition.

Park et al. [98] proposed an automatic traffic surveillance scheme to estimate significant traffic parameters from video frames retrieved through a single camera. They introduced a novel “linearity” characteristic in vehicle model which is different from the other traditional methods. In that approach the vehicles categorize as only cars and non-cars. The developed method was found capable of handling the issue of vehicle occlusions due to shadows, which regularly cause the failure of extra vehicle counting and classification. Researchers solved this issue by means of a new line-based shadow algorithm that employs a set of lines in order to remove every unnecessary shadow. The employed lines are created from the information of lane-dividing lines. A perfunctory system was implemented to detect the lane-dividing lines. The detected lane-dividing lines are able to give significant information for characteristic normalization, which are
able to make the vehicle size extra invariant, and hence recovers the accuracy of vehicle classification.

Yalçın et al. [99] presented an algorithm for vision-based vehicle detection and classification in monocular image series of traffic scenarios documented by a fixed camera. The raw images, region level, and vehicle level were applied. Vehicles are modelled as rectangular pieces with definite active behaviour.

Veeraraghavan et al. [100] proposed a feature based tracking method in order to track the vehicles under overcrowding. To make the scheme robust to biased occlusion, vehicle sub-features were tracked rather than tracking whole vehicles. The constraint of general movement was used to combine sub-features collect from the same vehicle.

Rivlin et al. [101] proposed a robust and real-time method for tracking vehicles and this algorithm includes two stages: object region extraction, vehicle tracking. Object region extraction is a notion of tracking vehicle is built upon the vehicle-segmentation technique. In relation to the sectioned vehicle shape, they proposed a three-step forecast technique on the basis of Kalman filter to track each vehicle.

Wedel et al. [102] presented a new non-parametric background model and a background deduction system. The model is capable of handling conditions where the back-ground of the image is cluttered and where it is not wholly immobile but includes small movements for example tree branches and bushes. The model estimates the possibility of watching the pixel intensity values on the basis of a sample of intensity values for every pixel.

Zhang et al. [103] presented a new algorithm for segmentation of intensity images which is robust, rapid, and free of tuning parameters. Their approach requires the input of a numeral of seeds, either individual pixels or regions, which will manage the creation of regions into which the image will be sectioned.
Wender et al. [104] presented a real-time scheme for pedestrian tracking in series of gray scale images obtained by a fixed CCD camera. The aim is to incorporate this scheme with a pedestrian manage scheme for junctions. The scheme outputs the spatio-temporal coordinates of each pedestrian in the time the pedestrian is in the scene. Three levels (raw images, blobs, and pedestrians) of processing is completed. Their scheme models pedestrians as rectangular pieces with a firm active behaviour. In order to estimate pedestrian parameters, Kalman filtering is used.

Zhang et al., [105] developed an end-to-end system for taking out the moving targets from a real-time video flow, categorizing them into predefined class in relation to image based properties. They applied their approach for vehicle tracking purposes. Examining pixel wise dissimilarity among successive image frames, the moving targets were detected. Classification metric were applied for classifying moving objects into three classes; human, vehicle, background clutter using a temporal consistency constraint. The targets (classified) were tracked by a fusion of temporal differencing and template matching.

Michalopoulos et al. [106] presented a method to classify and recognize moving vehicles in monocular traffic images. A common vehicle representation, symbolized by a 3D polyhedral representation depicted by 12 length parameters, was employed to cover the dissimilar structures of road vehicles. The object identification method is started by formulating a model hypothesis by means of a reference model and first values given by a movement segmentation step from a model-based tracking system depicted formerly. This model hypothesis was confirmed and the structure, the pose and movement parameters of the object were estimated concurrently. In this way, every related data from the image series calculated to this point were collected and employed for the structure parameter estimation and categorization of the moving vehicle.

Xie et al. [107] used the atmosphere state to model the relation among the objects and atmosphere, and incorporate it into the structure of Bayesian tracking. In addition, researchers presented a tracking technique for object tracking in structured atmospheres
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and used distance transform to model the atmosphere state as well as utilized particle filtering as the paradigm in order to solve the Bayesian tracking issue.

Cao et al. [108] presented a probabilistic method for automatically dividing foreground objects from a video frames. A region detection algorithm integrating edge information was initially proposed to recognize the ROI to save computation time and be robust to noise effects, within which the spatial relationships are symbolized by a region adjacency graph.

Gupte et al. [109] proposed a vehicle detection and classification system, in different methods by using various filters. They suggested that detecting the vehicles using Kalman filter method and background subtraction method, it will be easy to identify the vehicle and easy in the traffic flow.

Rashid et al. [110] used time-spatial image by presenting the detection and classification of vehicles from a video and it is the extension of the detection and classification of vehicles.

Cucchiara et al. [111] has worked on detecting moving vehicles at night. To achieve this, they represented a vehicle with only two points, and there was no information because authors treated the center of the headlight as a most important feature as well as extracted by morphological investigation.

Yu et al. [112] developed a hybrid model using landmark-based scheme and BS-Edge model to detect and shadow, which was further used to perform vehicle detection.

Mikic et al. [113] used the representation of the pixels’ color appearance for Classifying cast shadows from vehicles. Further, Cucchiara et al. [114] distinguished a cast shadow in a hue-saturation-value color space on the knowledge by proposing a deterministic method by means of the chrominance information, for instance the shadow
has comparable chromaticity however minor brightness than that of the similar pixel in the background representation.

Stauder et al. [115] recognized four criterions for background as well as light source, which are particularly for laboratory circumstances, however these criterion are not usually satisfied for outside images or sceneries.

Hansson et al. [116] presented a non-vision-based, dispersed real-time structural design for vehicle applications that includes both rigid as well as soft real-time processing.

McCall et al. [117] developed the "Video-Based Lane Estimation and Tracking" (VioLET) method and it is planned for lane-marking detection by means of steerable filters.

Borkar et al., [118] described a road detection scheme and in this the captured image processed pre-processing by using temporal blurring and gray scale translation. Then, Inverse Perspective Mapping was applied to remove perspective and transform the image into a bird’s-eye view. An adaptive threshold converted the grayscale image into binary and then a low-resolution Hough transform is computed to find a set of candidate lane markers. The candidate markers were further scrutinized in a matched filtering stage to extract the lane marker centres. Random Sample Consensus was used to estimate parameters for fitting a mathematical model through the recovered lane markers. Finally, the Kalman filter predicted the parameters of each lane marker line from one frame to the next.

Hsieh et al. [119] estimated traffic parameters from video frames by single camera, in order to achieve this, researchers presented an automatic traffic surveillance scheme and also proposed an automatic scheme to detect every feasible lane separating lines by examining vehicles’ trajectories.
Ajmal et al. [120] proposed a new algorithm based on image processing where aerial cameras for vehicle detection and classification particularly in main roads. In addition, this method was generally on the basis of morphological methods and moreover used thresholding and edge detection methods for vehicle detection.

Chai et al. [121] estimated the traffic parameters of vehicle motion by using an automatic vehicle classification and tracking technique at crossroads. This technique is on the basis of projective renovation of video frames and it is excellent capability to categorize detected vehicles and compute parameters of vehicle motion at crossroads.

Hu et al., [122] studied and examined various techniques of visual surveillance in dynamic scenes including modelling of surroundings, detection of movement, categorization of moving objects, tracking, understanding and explanation of behaviours, human recognition, and fusion of data from several cameras.

Lipton et al., [123] described an end-to-end technique in order to extract the targeted moving objects from a real-time video and that method classified objects based on image properties. Researchers applied a metric of classification to targets in order to classify targets as human, vehicle or background clutter, after classification with the combination of temporal differencing and template matching the targets were tracked.

Barnich et al. [124] presented a method for vehicle movement detection and that technique includes various inventive mechanisms.

Kothiya et al., [125] to identify or position the moving object in frame, the first step in the tracking is to detect the object. Later detected objects are classified as vehicles, human, swaying tree, birds and other moving objects. Collecting the objects in consecutive frames is the most challenging task in image processing. Due to complex object motion, irregular shape of object, occlusion of object to object and object to scene and real time processing requirements numerous challenges are exhibited. Some of the objects tracking usefulness are surveillance and security, traffic
monitoring, video communication, robot vision and animation. Their research presented object tracking in video footages through various image processing techniques in different phases.

Elgammal et al. [126] presented a background subtraction approach using a non-parametric background model. In that model, even though the scenes are messy and not utterly idle but contains very little motions such as tree branches and bushes can also have identified.

Manuel Vargas et al. [127] proposed a new background subtraction algorithm for the urban traffic scenes on the basis of sigma-delta filter. Since the original sigma-delta algorithm is an attractive alternative due to high computational efficiency. In complex urban scenes, due to the slow-moving or temporarily stopped vehicles, the background model is rapidly degrading because it is easily “contaminated”. Then to process the foreground detection mask, the consequent foreground validation steps are required. The proposed algorithm introduces a confidence measurement for each pixel in order to achieve a more stable background.

Zhang et al., [128] classified the motion in the scenes by using Bayesian framework and hence improved the robustness of the model. Also, the parameters of the model are estimated using EM algorithm. The direction and magnitude of the motion vectors are given as input to the Bayesian rule and EM algorithm.

Panda et al., [129] proposed a novel method for targeted object detection in the presence of background clutter such as leaves of trees and changing illumination condition in real-time video and then tracking the object. In their proposed method, spatial and intensity resolution of an image are reduced in order to decrease the effects caused by the background clutter. In addition, to detect a moving object 3-frame-differencing method was employed and moving objects from the background are segmented using Fuzzy c-means clustering.
Mehrubeoglu et al., [130] presented semi real-time vehicle tracking algorithm to determine the speed of the vehicles in traffic cam video. They used optical flow algorithm for the above purpose. The vehicle speeds in steady flow of traffic have been computed to within 5% of the speed limit on the analyzed highways in the video clips.

Indu et al., [131] presented velocity estimation method for ground vehicles. The vehicle detection and tracking was done using optical flow algorithm. The travelling distance of the vehicle is calculated by the moment of the centroid of the car overt the frames.

ArashGholami et al., [132] presented vehicle detection and speed recognition technique using background subtraction. The approach used is not affected by weather changes.

Gyaourova et al., [133] has studied object tracking in traffic scenes by utilizing block matching technique. Videos were captured by using a motionless airborne camera. For different resolutions and complexes also they have discussed the block matching technique.

Wang et al., [134] at first segmented image into foreground for each object of interest. Then for different possible directions of movement the changes in features of each consecutive frame were calculated. The position of the object in the next frame is decided by the certain threshold value.

### 2.2.2 Vehicle Classification

Nurhadiyatna et al., [135] focused on real time vehicle detection, feature extraction, and classification for multiple objects using a single stationary camera. The classification process is carried out in three main steps: Gaussian Mixture Model with Hole Filling Algorithm (GMMHF) for the detection of multiple vehicle; Feature extraction is performed by Gabor kernel; and third step is multi-class vehicle classification.
Ma et al., [136] applied vector sparse coding with linear SVM classifier to solve the vehicle classification problem. They applied SIFT to extract the local features of the vehicle image which (SIFT feature vectors) was then distinguished nonlinearly with sparse coding. In their approach at first, they projected SIFT feature vectors to a higher dimensional feature that eventually enabled resulting sparse code vectors more perceptible and thus linear SVM classifier was used to perform classification. In addition, they applied L2-norm constraint based vector sparse coding to perform vehicle classification.

Karaimer et al., [137] presented vehicle classification with omnidirectional cameras. They examined the performance of the combined shape-based and gradient-based classifiers. The omnidirectional video frames, obtained after background subtraction from the silhouettes were extracted for the shape-based classification and vehicle classification is performed with kNN (k Nearest Neighbors) algorithm. For gradient-based classification, they employed HOG (Histogram of Oriented Gradients) features. The features were extracted from the region located by the foreground silhouette. They used SVM classifier as the combination of HOG+SVM has been applauded for its efficacy.

Liu et al., [138] introduced a vehicle classification system on the basis of Dynamic Bayesian Network (DBN). They utilized three types of features in their system: vehicle’s geometrical characteristic, license plate location and shape, and the pose of the vehicle. It was then followed by feature extraction from the video sequences. The probability distributions of the features were established by GMM. They classified the vehicles into four classes: sedan, bus, microbus, and unknown.

Chen et al., [139] applied sparse learning to perform vehicle recognition and classification. In the dictionary images were labelled according to vehicle type after objects captured with a GMM background subtraction program. Later the images were decomposed and a linear SVM trained with the extracted feature for vehicle classification. Similarly, in [140] Peng et al., [140] proposed a vehicle classification
method based on sparse coding and spatial pyramid matching, by taking into account of vehicle image without assignment and complex influence caused by weather. In their model at first, they extracted patch-based sparse feature estimated with a discriminate dictionary. Later a spatial pyramid model was utilized by doubling the sparse feature to generate long sparse feature. The classification was computed by, SVM with the histogram intersection kernel.

Zhang et al [141] proposed an integrated vehicle detection and classification system and introduced a multi-resolution vehicle detection scheme as an improvement over the cascade boosted classifiers. The vehicle classification is based on the Classified Vector Quantization (CVQ). The justification of choosing CVQ is its advantages in providing classification confidence by incorporating rejection option. The significance of rejection in enhancing the system’s reliability is emphasized and evaluated.

Huet et al., [142] proposed the Haar features and HOG as useful features for vehicle detection respectively. They applied Haar and HOG features for vehicles identification in videos and classified them into two categories.

Peña-González et al., [143] presented a vision based system to detect, track, count and classify moving vehicles. They applied HD-RGB camera to retrieve vehicle data which was then followed by information processing using different clustering and classification algorithms.

Dong et al., [144] proposed an appearance-based vehicle type classification method from vehicle frontal view images. They used convolutional neural network to automatically extract excellent features for vehicle type classification. The network is pre-trained through the sparse filtering to capture interesting and discriminative information of vehicles. Network uses layer-skipping to ensure that final features contain both high-level global and low-level local features. Vehicles are classified by employing soft max regression after the final features are extracted.
Ma et al., [145] presented a method based on multi-feature fusion, which combines local feature and global feature together. After getting local information by SIFT, they extracted global feature by means of PCA. Then they combined the features using a multiple kernel framework with a SVM classifier.

Qian et al., [146] proposed vehicle classification model using deep network’s higher-layer features and traditional features. First, they extracted the traditional features of PHOG and LBP-EOH, which was then followed by estimation of the higher-layer features from the vehicle pictures using deep belief networks (DBN).

Gu et al., [147] proposed a vehicle size classification system for automatic reorganization of small-size, medium-size and big-size cars. In order to identify the small-size and big-size cars in large location, the proposed system employed the concavity property of sedans and buses. Then the head width of a car was evaluated and two aspect ratios of car height to head width and head width to car width were estimated. To perform vehicle classification based on different sizes, they applied multiclass SVM classifier.

Liang et al., [148] described algorithm that counts and classifies highway vehicles on the basis of regression analysis. In their proposed algorithm, there are mainly two contributions, first to identify the foreground segments, warping method was developed, that contain unclassified vehicles. Secondly a nonuniform mesh grid and a projective transformation were estimated to reduce vehicle distortion caused by the foreshortening effect and applied during the warping process.

Dong et al., [149] performed vehicle type classification using a semi supervised convolutional neural network (CNN) where the vehicle frontal-view images were used as input. In order to retrieve sufficient discriminative vehicle information authors introduced sparse Laplacian filter learning that enabled network-filters sufficient amounts of unlabelled data. In their model, they implementing SoftMax classifier at the output layer,
which was then trained by multitask learning with small amounts of labelled data, which was then followed by classification.

Dong et al., [150] presented a vehicle type classification method employing structural and appearance-based features. The structural feature which characterizes the spatial relative layouts of vehicle parts helps to distinguish a vehicle from the background, and the appearance-based feature is local and robust to the interferences of illumination variation and the background. To obtain compact and discriminative representations of vehicles, the distributions of these two types of features are computed. They further employed Multiple Kernel Learning to combine multiple distributions together for classifying vehicle types.

Sun et al., [151] explored deep learning concept for vehicle classification, where they applied DBN deep learning approach for classification. They trained DBN by numerous object representations comprised image pixel value, feature histogram by Histogram of Oriented Gradients (HOG) operator and eigen-features that eventually enabled classification of object as pedestrian, biker, vehicle and others.

López et al., [152] proposed a method for vehicle/pedestrian object classification. On the basis of learning of a static kNN classifier, a dynamic Hidden Markov Model (HMM)-based classifier, and the definition of a fusion rule that combines the two outputs. They studied the dynamic aspects of the moving objects by analyzed the trajectories of the features followed in the HOG-PCA feature space, instead of the classical trajectory study based on the frame coordinates.

Chen et al., [153] developed a real-time and vision-based vehicle classification and counting system. The proposed system involved creating Time-Spatial Images (TSI) from input video, by using the Support Vector Machine (SVM), removal of shadow portions in TSI and detection of Region of Interest (ROI) through a simple morphology process by Deterministic Non-Model Based Approach and finally utilizing the ROI
Van et al., [154] presented some methods of representing image's features that help detect and classify vehicles from video. Proposed method contains: shape representing method, dataset of vehicle that can be classified. In order to classify the type of object or different objects Parameters of the Image's length in combination with parameters of visual length of object were utilized.

Chen et al., [155] presented an algorithm for the semi-automatic annotation of vehicle type that significantly reduces the time needed to annotate a dataset. They used background subtraction GMM for automatic detection of vehicles. The detected vehicles are classified into four main categories: car, van, bus and motorcycle. Measurement-based features and an intensity-based pyramid HOG (histogram of orientation gradients) is employed to create vehicle observation vector. To initialize the labels of the collected data set K-means clustering is employed. In order to recognize the low confidence samples, the output scores of linear SVM classifier are employed, which were then annotated manually to reduce the number of samples requiring annotation.

Chen et al., [156] applied their model to segment moving road vehicles from the colour video data retrieved from static close circuit camera and classified vehicles in four categories like car, van and heavy goods vehicle. To perform vehicle segmentation, authors applied recursively updated GMM model enriched with a multi-dimensional smoothing transform. To perform classification, they applied a kernelised SVM model.

Li et al., [157] proposed a moving wheeled vehicle detection model and employed micro-Doppler features from returned radar signals in order to classify the vehicles within short dwell time. In their proposed method, Empirical Mode Decomposition (EMD) known as an adaptive analysis technique is employed to decompose the motion components of moving vehicles, and a
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Hierarchical classification structure using the decomposition results of returned signals is proposed to discriminate the two kinds of vehicles. By checking the existence of its unique feature, first stage of the structure elementarily recognizes the tracked vehicle data. Further the classification is carried out based on EMD which is implemented in the second stage by using Support Vector Machine (SVM) classifier.

Zhang et al., [158] proposed a robust and efficient classification model using cascade classifier ensembles. In their model, the first ensemble applied was heterogeneous that comprised numerous classifiers, including kNN, Multiple-Layer Perceptrons (MLPs), SVM, and random forest. In the second classifier ensemble second classifier ensemble of the classification was further improved which comprises set of base MLPs synchronized by an ensemble meta learning method called Rotation Forest (RF). In their model, for both of the ensembles retrieved rejection option by means of relating a degree of consensus from majority voting to a confidence estimates.

2.3 Summary

In this section, some of the key researches and proposed approaches discussing vehicle detection, tracking and classification were discussed. This is the matter of fact that a number of approaches have been applied to achieve these objectives; still there exist scopes for further optimization, particularly when the road traffic has to be considered with higher density, high speed moving vehicle, vehicle occlusion, different environmental conditions etc. With these objectives, this research work or the thesis proposes novel approach for vehicle detection, tracking and classification system. In addition, various other facilities such as vehicle speed estimation, vehicle counting etc. has also been proposed in this thesis.