

Navigation System for Autonomous Vehicle: A Survey

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ARTICLE INFO	ABSTRACT
Received: August 02, 2020	Advanced Driver Assistance Systems (ADAS) apply to various high-tech in-vehicle systems
Accepted: October 06, 2020	designed to enhance road traffic protection by making drivers become more mindful of
Volume: 2	the road and its potential hazards, as well as other vehicles around them. The design of
Issue: 2	traffic sign, traffic light, traffic cone, car, road lane, pedestrian and road blocker detection
	and Recognition, a significant ADAS subsystem, has been a problem for many years and
KEYWORDS	thus becomes an essential and successful research topic in the field of smart transport
	systems. This paper present different approaches Devised over the last 3 years for the
Traffic Sign, Traffic Light, Road	diverse modalities. We present a survey of each challenge in form of table in terms of
Lane, Pedestrian, Cone, Car,	"algorithm, parameter, result, advantage, and disadvantage. For each survey, we
Machine Learning, Deep	describe the possible implementations suggested and analyze their underlying
Learning, Autonomous vehicle,	assumptions, while impressive advancements were demonstrated at limited scenarios,
Driverless Car	inspection into the needs of next generation systems reveals significant gaps. We identify
	these gaps in disadvantage block and suggest research directions that may bridge them.
	we identify the future solutions proposed and examine their underlying assumptions,
	although promising development has been shown in restricted contexts, analysis of next-
	generation applications requirements shows significant gaps. We define certain holes in
	the block of drawbacks and propose avenues for work that can cross them.

1. Introduction

Since the mid-1980s several institutions, research centers, car companies, and businesses from other sectors around the world have been researching and designing self-driving cars (also known as autonomous cars and driverless cars). In the last decade, the Defense Advanced Research Projects Agency (DARPA) sponsored three contests to accelerate technologies for the production of self-driving cars. The first, called the DARPA Grand Challenge, was realized in 2004 at the Mojave Desert, USA, and required self-driving cars to navigate a 142-mile long course across desert trails within 10 hours of time. Within the first few miles, all competing cars had failed. Repeated in 2005, the DARPA Grand Challenge (Buehler et al., 2007) allowed self-driving cars to negotiate a 132-mile long route across lakes, dry lake beds, and mountain passes, including three short tunnels and more than 100 fast left-and right turns. The third challenge, known as the DARPA Urban Challenge, took place in 2007 at the former George Air Force Base in California, USA, which allowed self-driving cars to negotiate a 60-mile-long route through a virtual urban environment, along with other self-driving and human-driven vehicles, within a 6-hour time limit (Wikipedia,2020).

The autonomous vehicles technology is increasing day by day. To drive a vehicle on road the vehicles must detect road edges, road lanes, road obstacle, pedestrian detection and traffic sign recognition. Each year approximately 1.3 million peoples are killed worldwide on roads, and among 10 to 50 million are injured due to road accident. A worthy explanation to this problem to develop machines, which cares for the environment. Due to this reason today, safe vehicles driving is charming a standard topic in many fields, from small projects to large automobile industries (Duan.j and Viktor.M, 2015). The technology of digital cameras is developing so fast. The progressive studies on camera-based observing and results are uses for benefit of humankind. Such as, the developments of computer vision and image processing are broadly used in the area of security. The improvement of cameras for road lane detection is also very useful to increase visibility. And we can drive more safely. One of the supporting technologies that extremely contribute to an Advanced Driving Assistance System (ADAS) is road lane detection. In general, significant traffic information presented to drivers is typically interpreted as visual signals such as traffic signs, traffic lights, road markings, traffic cones, pedestrian identification, vehicle detection etc. In certain cases, certain causes such as

tiredness, drunk driving and driving anxiety may affect human visual perception. An ADAS will recognize this visual language in order to improve road safety and pass the information on to users using various approaches to traffic sign identification.

This paper discus different works and the sample description is as follows: in the next subsection we define road lane, traffic sign, pedestrian, traffic light, traffic sign, and car Detection role and link it to requirements of the automotive industry also provide a comprehensive overview table of each paper in sequence which consist more information such as "author name, title of research paper, work on , advantage, disadvantage and also discus result of relevant paper". In last session concludes the Survey with a summary and suggestions for future directions.

2. Surveys of Recent Challenges

The general approach for navigation system detection, recognition and classification is, by dividing the task in to seven stages; traffic light, traffic sign, pedestrian, car, traffic lane, cone and road blocker detection stage and the classification (or recognition) stage.



Figure 1: Autonomous Vehicle Navigation System

2.1 Road Lane

Road and Lane perception via the traditional cues remain therefore the most likely path for autonomous driving. Road lane understanding include detecting the extent of the road, the number and position of lanes, merging, splitting and ending lanes and roads, in urban, rural and highway scenarios. Although much progress has been made in recent years, this type of understanding is beyond the reach of current perceptual systems.

There are numerous sensing methods used for road lane detection such as monocular camera (Choi, 2019), LIDAR (Feng, 2018), Radar sensors (Song, 2018) to obtained data from vehicle inertial measuring unit (IMU) with global positioning information using the Global Positioning System (GPS) (Su, 2017) normal map (Xing, 2018) digital map (Yuan, 2018) and space map

(Andrade,2018). For line segmentation from the input dataset use Deep convolution neural network (CNN) (Dhall,2019) and probabilistic voting procedure (Hoang,2019) to reduce the computing costs in the estimation of the vanishing point. Real-time vision-based lane detection algorithms are used to segment lanes from the road which can be done by Kalman Filter algorithm (Küçükmanisa,2019) and Hough Transform (Lee,2018). In addition, a reliable lane detection filter based on the Fuzzy Inference method, which requires three input parameters, the preceding being the difference between a line, the pixel deviation between the left and right neighbors, in a learning process is proposed in paper (Ouyang,2019).

S.NO	Work on	Methodology	Parameter	Result	Advantage	Disadvantage
			Obtained			
[3]	Lane	Robust lane	Color	97 %	In the vanishing point,	Aim to determine right
	Detection/	detection method,	based		a system using a	lanes that are well
	2017	Vanishing Point			lookup table is	ahead of the car in a
		Estimation.			proposed to reduce	long distance. Extend
					the computing costs.	the suggested solution
						to unstructured path
				-		identification as well.
[4]	Lane	Semi-Global	Camera	99%	Traffic lanes model	To achieve a better
	Detection/	Matching (SGM)	navigation		with a full chance	outcome, plan to
	2018	algorithm, Canny			angle in Hough Space,	combine this approach
		algorithm, IPM			and complex pole	with an interactive
		algorithm, Hough			identification ROIs,	database, or GIS.
		Transformation and			which is resilient to	
		Lane Detection, CNN			road bumpiness.	
[5]	Lane	Deep CNN,	Region	N/A	Low response time	Quality may be
	Detection/	YCbCr color space -	based		and Extreme CNN	influenced by different
	2019	Local adaptive			Lower performance-	environmental factors,
		threshold, VPGNet,			based approaches in	and additional pre-
		BING and PCANet,			extreme conditions,	processing technique
		DVCNN			resistant to various	is needed.
					forms and sizes of	
					road markings.	
[6]	Lane	Odometer and IMU,	Lane	99.9	Precise, accurate and	Sadly, regional maps
	Detection/	reference path, the	marking	%	detailed	providers cannot be
	2017	lane markings, Dead			understanding of lane	used because they
		Reckoning, Lane			markings developed	don't provide precise
		Marking Detector,			from a monocular in	description of lane
		and the GNSS stamps			the vicinity of the car.	markings.
[7]	Lane	Stereo Camera, v-	Camera	98.69	This approach will	The challenges facing
	Detection/	disparity image,	navigation	%	achieve good	the lane identification
	2017	Hough transform			detection efficiency	and monitoring
		method, texture-			without considering	algorithm include lack
		based method, visual			any parametric lane	of lane marking
		odometry (VO)			model for both	accuracy, poor
		method, Dijkstra			straight and curved	visibility due to bad
		shortest-path model,			lanes.	weather, lighting and
						light reflection,
						shadows and thick
						road-based guidance.
[8]	Lane	Straight-curve line	Bent	92-93	Improving the	Improving the
	Detection/	detection, Curve	model	%	successful protective	efficiency of this
	2019		navigation		driving and aided	device relates directly

Table 1 : Road Lane Navigation system for Autonomous Vehicle

		prediction based on straight curve, Lane deviated angle warning			driving of the automobile which is under inclined road conditions is of considerable importance.	to the precision of lane identification. A fuzzy inference system-based filter for efficient lane identification needs to be studied for this.
[9]	Lane Detection/2018	Otsu's method, Elimination of edge noise, Hough Transform, least square method	Region and map	93.60 %.	This method provides more reliable results in different light or crowded traffic conditions.	The time factor for mobile devices can be reduced and the detection rate increased in more complex scenes.
[10]	Lane Detection/ 2019	FAST-based, YOLOv3,	Map based	99%	Map matching localization system which detects multi- stage road facilities and slowly reduces the ambiguity of position.	Endpoints are wrongly identified in the continuous photos, instead of defining the ego-lane along the time axis in one trial strategy to study the process that accumulates the effects of the ego-lane ident cation.
[11]	Lane Detection/ 2018	ED Lines method, Kalman filter, ROI algorithm, Canny edge detection and the PPHT, A-ROI, Hough transform	Video based	99%	Algorithm gives accurate results with low computing power.	The developments in this area in the potential viewpoint would bring these devices to the point of automated and cooperative driving, focused on sensor networks and sensor fusion.
[12]	Lane Detection/ 2018	(CODEC) encoding Process, approach Gamma Correction, Brazilian Transit Code (CTB), IPM algorithm adequate method, Canny filter, Hough transform (HT) algorithm,	Obverse monocular camera	98%	A creative lane identification and monitoring technique, which suits as a technical prerequisite for implementing DAS apps such as Lane Departure Alert.	Because of the broad information history and the low cost of camera equipment a substantial number of existing studies rely on researching vision- based lane detection methods.
[13]	Lane Detection/ 2018	Integration Methods Introduction, Vision- Based Lane Detection Systems, deep learning Models, (GAN),	parallel Navigation	N/A	There is a large volume of literatures that use vision-based algorithms because of the low cost of camera equipment and extensive background awareness in image processing.	In heavy traffic and adverse weather conditions, the huge challenge for potential vision-based systems is to retain stable and reliable lane dimensions.

[14]	Lane	RCS, RCS, Static	Lane	N/A	Using vehicle radar	Further improvement
	Detection/	Points Extraction,	detection		sensors, sense the	of the clustering
	2018	Hough Transform,			lane boundary by	algorithm, monitoring
		Pattern Extraction.			changing the current	techniques can be
					road markings and	used to render
					show and verify the	identification more
					effectiveness of road	reliable and to reduce
					marking.	the technical
						necessity.
[15]	Lane detection/	fuzzy filter	Clustering	N/A	This technique is	Detection of road lane
	2019				computationally	markings, and
					lightweight, and is	recognition of arrows
					ideal for software and	and bike marks did not
					computers in real	receive sufficient
					time.	consideration needs to
						be enhanced.
[16]	Lane detection/	deep CNN, Road	Color	N/A.	Because of this	Nevertheless, lane
	2019	RMN, SBD method.	based		method the	identification remains
					computing expense	an unsolved issue, let
					has improved	alone other road
					significantly, which will	direction markers,
					also affect the	owing to the difficulty
					accuracy of the ballot.	of recognition
						precision in different
						driving scenarios.

2.2 Traffic Cone

Intelligent technology like object recognition is becoming an increasingly hot topic in research on autonomous vehicles. Among the many objects it is important to recognize the traffic Cone as a guided Traffic Sign. Interestingly, these road Cones are static objects but they are frequently replaced and relocated around the urban driving scenario.

The traffic Cone detection and location of traffic cones is necessary for autonomous vehicles. The volatile conditions of light and the weather are a big challenge. A variety of realistic methods such as color space selection, segmentation, shape analysis, distance estimation, and detector training are combined to ensure good detection rate and localization accuracy (Yong,2015). A way of finding out where the impasse is in the image and of recognizing if it is the cone (Yoo,2017), based on the fusion of information between vision and Radar sensors. In addition, an object category that is important to autonomous traffic control is to examine traffic Cones. Intrinsically, 3D object detection using monocular camera images is an unplaced problem. In this study, take advantage of the unique traffic cone structure and suggest a pipeline approach to solve this issue (Zhang,2019).

S.NO	Work	Methodology	Parameter	Result	Advantage	Disadvantage
	on		Obtained			
[17]	Traffic	Extraction by	Region	88.0%	Real-world conditions show	In addition, this solution will
	cone/	color distance,	based		that the proposed method	be evaluated on this
	2014				will meet the requirement	autonomous vehicle
					for realistic competition in	platform, which shows both
					terms of detection and	reliability and instantaneity
					position.	of the guarantee.
[18]	Traffic	Chamfer	Video	90 %	The suggested algorithm	Future work should
	cone/	matching, Edge	based		effectively and in real time	concentrate on more specific
	2015				senses cone by combining	objects such as pedestrians

Table 2:Traffic Cone Navigation system for Autonomous Vehicle

		detection,			input from two sensors: the	or cars based on this
		threshold			radar and video.	approach.
[19]	Traffic	structural	3d Traffic	N/A	Proposed pipeline is tested	Use this algorithm in video
	cone/	regression	cone		to show performance and	processing to make it
	2019	network,			precision on a real-time,	possible to actually apply
					automated racing car.	software in a more practical
						way.

2.3 Traffic Light

Traffic Lights detection (TLs) for a temporary time between manually operated cars and a fully autonomous car network is an integral part of Driver Assistance Systems (DAS). The urban environment has many challenges for all parts of the DAS, in particular for systems relying on computer vision. The detection and recognition of TLs at intersections is one of the most important challenges. The conventional resolution of traffic light detection with cameras however, has led to the publication of many interesting approaches in the field of pattern recognition.

The positions of the TLs can be found easily in the image by conducting horizontal and vertical position (Zhou,2014), Deep Neural Network (CNN) (Ali,2017), shape-based segmentation (Kulkarni,2018) with efficient object detectors, Single Shot Multibox Detector (SSD) (Ozcelik,2017), Region-based Convolution Network (R-CNN) (Prabhakar,2017) and color-based segmentation. After the position of the TLs in the image is determined, color of the TLs is easily evaluated by SVM classification model, (Rajapaksha,2018). Real-time detection of TLs from images and takes advantage of a deep point-based detection architecture (Ali,2018), and RFID (Bruno,2018) to prevents problems that normally exist with ordinary TLs recognition systems and position of TLs is used as a landmark utilizing a traffic lights chart with substantial visual characteristics throughout the urban environment (Bruno,2018).

S.NO	Work on/year	Methodology	Parameter Obtained	Result	Advantage	Disadvantage
[20]	Traffic light /2017	R-CNN	High speed autonomous vehicle	73.2 %	This design, using an efficient GPU, fast enough frame rate, shows the suitability of the device for automated highway driving cars.	Using a much broader network model such as Google Web, the performance can be further improved.
[21]	Traffic light /2017	HSV, Raspberry Pi	Color	N/A	Detection and identification of fast, reliable and real-time automated traffic signs will help the driver and improve driving.	Differences in light intensity and shadows created by the presence of objects are just a few of the major issues this approach faces. For a system which is more effective.
[22]	Traffic light	Candidate region selection, k-means clustering, Black box selection, HSV color	Shape	96.2 %	It is very efficient to find the center pixels with k-means also this algorithm only performs Operation on a small candidate.	To find a better solution, further studies should be conducted with adaptive thresholding methods.
[23]	Traffic light /2019	The CNN classifier,	Video deep learning	96.6%)	Overcome low versatility and accuracy of deep learning methods focused on vision and	Alternatively, after the vehicle stops, use the gap between the vehicle and the stop line as another

Table 3: Traffic Light Navigation system for Autonomous Vehicle

					high-power	indirect measure to
					consumption of	check the process.
					heuristic algorithms.	
[24]	Traffic	SSD, Spatiotemporal	Large dataset	84.20 %	Recent developments	More modern
	light	filter,	-		indicate that deep	architecture can provide
	/2018				neural networks are	better detection
					commonly utilized on	accuracy, such as Mask
					their own vehicles.	R-CNN.
[25]	Traffic	Frequency	Traffic light	Shape	This solution	A deep learning
	light	Identification (RFID)	detection	and	eliminates problems	algorithm should design
	/2017			deep	usually faced in	for detection and
				learning	ordinary traffic light	classification using a
					recognition schemes.	regional CNN trained.
[26]	Traffic	R-CNN, faster R-CNN	Obstacle	73.2 %	This design, using an	Using a much broader
	light		detection		efficient GPU, fast	network model such as
	/2017				enough frame rate,	Google Web, the
					shows the suitability	performance can be
					of the device for	further improved.
					automated highway	
					driving cars.	
[27]	Traffic	CNN classifier, R-	Dynamic	96.8%	Important for	Future examination will
	light	CNN, YOLOv2, and	Range		autonomous vehicles	investigate the use of
	/2018	SSD			because it could cause	both dark and light
					a red light to turn into	photos as contributions
					a deadly car accident.	to the CNN network and
						will hold both contextual
[20]						color and shape details.
[28]	Irattic	fully convolutional	Clustering	N/A.	Recalling traffic light	A classification stage
	light /2018	network (FCN),			identification is higher	should be introduced for
	/2018				than SSD and greater	the identified areas.
		DBSCAN algorithm			than 0.9 for both	
					testing and training	
[20]	Troffic	CNN Factor & CNN	Maying	00	applications.	Can also sustamiza tha
[29]	light/	CININ, FASLER F-CININ,	vehicle	33	nrocess by moving	system to ensure safe
	11g117		venicie		information increases	driving It may also be
	2010				the performance of	fitted with the ability to
					the framework for	respond to spoken
					real-time applications	orders or hand signals of
					rear time applications.	law enforcement or
						highway safety
						employees
[30]	Traffic	Vision-based	Region based	N/A	Once the map is built	Boost precision, and
[20]	light/	localization. RTK-		,,	correctly, a low-cost	combine certain forms of
	2018	GPS, IMU, sensor			camera will help the	spatial positioning. V2V
	-	fusion, traffic light.			vehicle easily locate	methods of localization
		Kalman filter, inertial			itself in low signal	may be a good choice for
		navigation.				achieving good accuracy.

2.4 Traffic Sign

Advanced driver assistant system plays important rule in the area of automatic traffic sign detection and recognition (TSDR). Driving on correct lanes and limitation of speed and preventing obstacles, tracks for footmen, direction of destination, road access, current traffic condition etc. have been provided with important visual information by traffic signs for helping drivers in driving scenario.

Traffic sign detection and recognition in complex road scenarios is to achieve high performance in a low-cost system. To detect and recognize sample road signs and modern 3D signs (Ghallabi,2019) by using RFID-based system, neural network (NN) (Sari,2018), Deep Learning technique (Slavescu,2018) and CNN. Also, it can be detected by digital GPS maps (Luong,2017) color probability such is HSV (Gao,2018), Histogram of Gradient (HOG), Local Binary Patterns (LBP) (Guo,2019) combined with SVM classifier to eliminate all incorrect candidates (Navarro,2017). Further, traffic signs classification based on transfer learning (Temel,2019) to address the vulnerabilities in current databases by implementing the CURE-TSD Real dataset (Uçar,2017).

S.NO	Work on	Methodology	Parameter Obtained	Result	Advantage	Disadvantage
[31]	Traffic sign/ 2017	radio frequency identification technology (RFID) technology	Shaped based	N/A	Avoids problems usually encountered with ordinary traffic light recognition systems	Still be a challenge for researchers and manufacturers to be able to apply in reality due to the strict requirements of the correct rate.
[32]	Traffic sign/ 2018	Deep Learning;	2D and 3D	98.3%	This enabled traffic signs to be detected in the most varied types of situations, and also with greater robustness when compared to other methods.	In future works intend to work with systems of visual attention, considering the context / zones of the scene and the fuzzy logic in order to better define the regions.
[33]	Traffic sign/ 2018	DCNN classification	2D and 3D	99.1 %	It allowed traffic signs to be identified in the most diverse types of situations and also with greater robustness relative to other approaches that only use 2D data.	Working with visual attention technologies, considering the context / zones of the scene and the fuzzy logic to better define the regions where traffic signs are required, thereby allowing us to develop the robotic computer vision system to detect and classify the most important signs.
[34]	Traffic sign/2019	Haar-cascade,	Neural network	N/A	This will reduce the number of injuries, effectively reducing the time lost during transportation	The number of loops done on the map can be improved to improve the accuracy of autonomous driving for effective level 5 autonomous car programmed.
[35]	Traffic sign/ 2018	Edge detection contour Detection, color filtering,	Shaped and color based	87.36 %	Bring us to eliminate standard methods for image processing and use recurrent neural networks.	Further decline in performance of the model may be eliminated.
[36]	Traffic sign/ 2019	CNN	Deep learning	83.7%.	Classify them correctly using Convolutional Neural Network to capture traffic signs, and respond to them in real- time.	RCNN can be used for further accuracy.
[37]	Traffic sign/2018	Raspberry Pi	Real time shaped based	N/A	Using a simulated GPS, designing a miniature self- driving vehicle was able to position the car and navigation on the race track.	Unmanned driving networks, real- time identification and effective traffic sign awareness are among the main concerns. For further research a radio-controlled vehicle is therefore proposed.
[38]	Traffic sign/ 2019	GNSS (Global Navigation Satellite Systems).	Region based	N/A	The proposed system expands the research in which a lane marking based localization program was created.	An image module to incorporate a visual-based localization will be included in future work.

Table 4: I rattic Sign Navigation system for Autonomous vehicle	Table 4:Traffic	Sign Navigation	system for	Autonomous	Vehicle
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[39]	Traffic	Raspberry Pi	Real time	N/A	This method is used when	Variations in light intensity and
	sign/ 2017		Color and		the vehicle depending on	shadows formed due to the
			shaped based		traffic lights has to take	presence of objects are just a few
					diversions and start /	of the biggest problems this
					stop.	method faces.
[40]	Traffic	HSV, Histogram of	From Moving	98%	Good performance even	This algorithm can be used in video
	sign/ 2017	Oriented	vehicle color		in complicated	processing to make the program
		Gradients (HOG),	based		backgrounds and	more realistic in practice.
		adaptive threshold			overlapped signs in most	
		method, SVM			test cases.	
[41]	Traffic	Histogram of	Distance	96%	The distance calculation,	More work includes gathering the
	sign/ 2018	Oriented	based		which is an essential	complete data collection for
		Gradients (HOG),			parameter in controlling	preparation, checking and
		deep learning			an autonomous vehicle's	evaluation using the prototype
		approach,			longitudinal velocity.	vehicle's Point Grey system.
		machine learning.			, ,	
[42]	Traffic	deep learning,	Blocked sign	96.34%	Proposing an OSCN model	In addition, various pre-trained
	sign/ 2019	OSCN			for determining the	deep learning models may be used
		model			occlusion of a road sign	to extract image features and
					and ensuring appropriate	further increase the accuracy and
					protection of road signs.	recall of the occluded classification
						of road signs.
[43]	Traffic	Benchmark	Haunted	68%.	This method explores the	Future work, adaptive pooling, and
	sign/ 2018	Algorithms,	characteristic		results of spectral analysis	spectral processing with no
		convolutional	variation		of challenging conditions	context are exciting avenues for
		neural networks			and reveals that the	study that can be further explored
		(CNNs)			challenging conditions will	to predict detection.
		. ,			contribute to distinct	
					magnitude spectrum.	

2.5 Pedestrian Detection

In year 2019 self-supporting vehicles on the roads are more popular, their success draws attention to safety issues for vulnerable road users such as pedestrian. Autonomous vehicles as driverless cars, pedestrian recognition and monitoring have received significant attention and are also rising rapidly with the advancement of self-driving techniques, it as one of the major issues for autonomous vehicles. While the work around pedestrian detection using vision-based approaches has expanded.

3D LIDAR, SVM-trained Classifier (Wang,2017), KNN, NBC (Chen,2019), local multiple Convolutional Neural Networks (LM-CNNSVM) (Das,2017) and CNN (Gao,2018) will be used to identify pedestrians and alarms will be generated when pedestrians are detected on the road. Another strategy is suggested in (Li,2018) which has reduced the computation complexity based on extraction of features such as color image, discrepancy map, thermal data (Qu,2016).

S.NO	Work on	Methodology	Parameter	Result	Advantage	Disadvantage
			Obtained			
[44]	Pedestrian	radial basis	3D LIDAR	N/A	For applicants who	Includes applying the
	detection /	function (RBF)			become too close to	algorithms proposed in
	2018	kernel, SVM,			the autonomous	this paper to sparse
		GPS, IMU and,			moving vehicle,	data, recognizing other
		DMI, Hash table			where only a few	interested objects such
		techniques			laser beams are	as cars and bicycles etc.
					irradiated on	its batter to detect with
					pedestrians, the true	machine learning
					positive rate is	approach.
					increased.	

Table 5:Pedestrain Navigation system for Autonomous Vehicle

[45]	Pedestrian detection/ 2016	Machine learning algorithm, (KNN), (NBC), and (SVM).	Machine learning 3D range	96.2%	The use of such histograms is one of the most significant developments in developing algorithms that track pedestrians.	Not only for people but also building thinking machines capable of detecting and understanding certain critical items in the image, such as motorcycles, vehicles, traffic signs and lights, etc.
[46]	Pedestrian detection/2017	Convolutional neural networks (CNNs), Local multiple system (LM-CNNSVM)	Deep leaning	92.80%	Incorrect entity identification and object detection, which can contribute to the prevention of harmful accidents by implementing a LMCNN- SVM program.	The range is related to the Red Green Blue (RGB) data and fed into a deep CNN to improve the accuracy and time complexity generating a point cloud of LIDAR data up sampling and translating into pixel- level detail.
[47]	Pedestrian detection/ 2018	RGB-LIDAR dataset to train CNNs,	Camera navigation	96 %	This approach is also implemented to maintain equal precision of classifying items and minimum damage.	Real-world tests will be carried out and the capacity of the conceptual method to identify artifacts in an autonomous vehicle environment based on a vehicle domain controller will be tested.
[48]	Pedestrian detection/ 2018	R-CNN, Fast R- CNN, Faster R- CNN, R-FCN.	classification	95.0%	After this, designation approach eliminates wasteful operations in pedestrian identification.	To build an autonomous vehicle speed control algorithm, implement an updated value-sensitive architecture approach to safely navigate the occluded pedestrian crosswalk.
[49]	Pedestrian detection/ 2019	HOG, SVM, CCF, AdaBoost	Camera	90 %	Combining color and thermal results, and adding variance as an additional function, achieves the best performance.	Certain specialized techniques for collecting and classifying features will be called to further improve performance of the pedestrian detector.
[50]	Pedestrian detection/2018	(POMDP), QMDP,	From moving vehicle	N/A	The public would certainly evaluate an autonomous vehicle on similar values after such as health, legitimacy and mobility.	Through integrating stereo vision cameras with thermal camera, while traveling on city roads, a car design is created from the data recorded from the test

2.6 Car Detection

Autonomous vehicles have received greater attention, since safety is of supreme importance. In addition, significant progress in software and hardware allows driving to develop into a smarter and more independent stage. Autonomous vehicles basic requirements are that vehicles can be followed safely and that appropriate measures are taken to prevent rear-end collisions and injuries. Detection of moving vehicles is an important part of aerial visual surveillance systems since vehicles are often very interesting objects. Moving identification of vehicles remains a difficult job.

A real-time approach to detect a car with high speed in image is based on color and distance measurement (Surinta,2019), Neural network convolution (Bougharriou,2017), Hungarian algorithm approach (Do,2017). Vehicles can be detected robustly by using the deep classifier by integrating multi-layer LIDAR (Li,2018) and to adjust road orientation V-J vehicle detectors are used to rotate images with high precision rate (Navarro,2017). To successfully detect a vehicle in urban environments for autonomous driving systems by using HOG and SVM (Xu,2016), Super-Resolution Convolutional Neural Network (SRCNN). To increase detection accuracy rate by using deep neural net- work algorithms such as YOLOV2 (Yang,2018) and YOLOV3 (Zhang,2018).

S.NO	Work on	Methodology	Parameter	Result	Advantage	Disadvantage
[51]	Car Detection/ 2016	Template matching approach, RANSAC algorithm, Frame difference method, Deep convolutional neural network	Moving vehicle detection	90%	The method is capable of processing real data rapidly, which will enable UAVs to automatically identify moving vehicles.	Focuses on improving classification process precision. More photos are needed to expand the dataset for different categories.
[52]	Car Detection/ 2018	VGG-16 Convolution layer, Multi-level feature fusion, RPN binary classification	Vehicle Detection	67.4%	proposed method incorporates optimization identification and monitoring and fast detection speed	Locate more efficient vehicle tracking strategies in UAV traffic images.
[53]	Car Detection/ 2019	Haar cascade classifier, max- margin, convolutional neural network- based features (MMODCNN), HSV color space	People and object detection	N/A	The project findings can be acknowledged to conform to the smart- city's surveillance of people and objects.	Build with a particular UAV platform which can adjust the camera angle.
[54]	Car Detection/ 2019	Canny, Hough transform, correlation filter- based vehicle detection	Vehicle detection and Lane detection	96.4%	The approach suggested also applies to various systems which detect objects such as pedestrians, traffic lights.	In addition, conceptual algorithm for an autonomous unmanned aerial vehicle (UAV) to identify and monitor individuals and automobile.
[55]	Car Detection/ 2016	combining IBEO, Sensor fusion, adaptive road segmentation method, Fast vanishing point ROI convolutional neural	Based Brake- Lights Recognition	99%	Such work is worth undertaking, because it could significantly reduce the identification errors induced by the illumination.	Tools that can reduce the cost of computing very deep CNNs while not rising error could be explored.

Table 6:Car Detection Navigation system for Autonomous Vehicle

[56]	Car	Viola-Jones obiect	UAV Image	92.49%	The improved V-J	Future research will
[]	Detection/	detection scheme.			approach provides good	focus on expanding
	2016	road orientation			performance on both	existing methods of
		adjustment			traveling and static UAV	identifying certain
		method, and			platforms.	modes of
		Enhanced viola-				transportation.
		jones.				
[57]	Car	Candidate Targets	Multiple	N/A	Results of the	The next stage is to
	detection/	Clustering	Moving Target		experiment	examine the 3D
	2017	morphological			demonstrate that the	attribute of different
		closing, GNN			algorithm can control	types of artifacts and
		method, Extended			abundant goals in real	classify object
		Kalman Filter.			time with performance.	classifications.
[58]	Car	Otsu binarized,	Improvement	87%	The current work	The most critical
	detection/	Histogram optical	and Passing		suggested an add-on to	solutions needed to
	2017	flow, Accurate	Vehicle		some particular	be implemented are
		bounding box	Detection		algorithm based in ML	vision-based driver
		Localization for			or non-ML, but the	assistance services.
		accurate distance			concept of motion was	
		measurement			also built on	
					mathematically.	
[59]	Car	Gradient	Shape based	83 %	Increased the	There should be
	detection/	histograms, Support	classification		performance of	environmental factors
	2017	Voctor Machines			proposed vehicle	that boost system
	2017	vector machines				
	2017	vector machines			detection system	performance and
	2017	vector machines			detection system	performance and make the system
	2017	vector machines			detection system	performance and make the system more resilient.
[60]	2017 Car	YOLOv2, k-means	Video based	61.34%	detection system Improve the accuracy of	performance and make the system more resilient. More Convolution
[60]	2017 Car detection/	YOLOv2, k-means algorithm, Hard	Video based detection	61.34%	detection system Improve the accuracy of identification while	performance and make the system more resilient. More Convolution Networks can be
[60]	Car detection/ 2018	YOLOv2, k-means algorithm, Hard Negative Mining	Video based detection	61.34%	detection system Improve the accuracy of identification while maintaining good	performance and make the system more resilient. More Convolution Networks can be called to improve the
[60]	Car detection/ 2018	YOLOv2, k-means algorithm, Hard Negative Mining deep learning,	Video based detection	61.34%	Improve the accuracy of identification while maintaining good detection efficacy.	performance and make the system more resilient. More Convolution Networks can be called to improve the performance of the
[60]	Car detection/ 2018	YOLOv2, k-means algorithm, Hard Negative Mining deep learning, Detection tuning	Video based detection	61.34%	detection system Improve the accuracy of identification while maintaining good detection efficacy.	performance and make the system more resilient. More Convolution Networks can be called to improve the performance of the design features built
[60]	Car detection/ 2018	YOLOv2, k-means algorithm, Hard Negative Mining deep learning, Detection tuning	Video based detection	61.34%	detection system Improve the accuracy of identification while maintaining good detection efficacy.	performance and make the system more resilient. More Convolution Networks can be called to improve the performance of the design features built into the deep
[60]	Car detection/ 2018	YOLOv2, k-means algorithm, Hard Negative Mining deep learning, Detection tuning	Video based detection	61.34%	detection system Improve the accuracy of identification while maintaining good detection efficacy.	performance and make the system more resilient. More Convolution Networks can be called to improve the performance of the design features built into the deep network.
[60]	Car detection/ 2018 Car	YOLOv2, k-means algorithm, Hard Negative Mining deep learning, Detection tuning yolov3 network,	Video based detection Based on	61.34% 97.4%	detection system Improve the accuracy of identification while maintaining good detection efficacy. Intensive transfer-	performance and make the system more resilient. More Convolution Networks can be called to improve the performance of the design features built into the deep network. Detection efficiency is
[60]	Car detection/ 2018 Car detection/	YOLOv2, k-means algorithm, Hard Negative Mining deep learning, Detection tuning yolov3 network, deep neural	Video based detection Based on Satellite image	61.34% 97.4%	detection system Improve the accuracy of identification while maintaining good detection efficacy. Intensive transfer- learning is implemented	performance and make the system more resilient. More Convolution Networks can be called to improve the performance of the design features built into the deep network. Detection efficiency is far from acceptable
[60]	Car detection/ 2018 Car detection/ 2019	YOLOv2, k-means algorithm, Hard Negative Mining deep learning, Detection tuning yolov3 network, deep neural network, Sample	Video based detection Based on Satellite image	61.34% 97.4%	detection system Improve the accuracy of identification while maintaining good detection efficacy. Intensive transfer- learning is implemented to improve accuracy of	performance and make the system more resilient. More Convolution Networks can be called to improve the performance of the design features built into the deep network. Detection efficiency is far from acceptable relative to the results
[60]	Car detection/ 2018 Car detection/ 2019	YOLOv2, k-means algorithm, Hard Negative Mining deep learning, Detection tuning yolov3 network, deep neural network, Sample Expanding for the	Video based detection Based on Satellite image	61.34% 97.4%	Improve the accuracy of identification while maintaining good detection efficacy.	performance and make the system more resilient. More Convolution Networks can be called to improve the performance of the design features built into the deep network. Detection efficiency is far from acceptable relative to the results of detection on
[60]	Car detection/ 2018 Car detection/ 2019	YOLOv2, k-means algorithm, Hard Negative Mining deep learning, Detection tuning yolov3 network, deep neural network, Sample Expanding for the Intensive Transfer	Video based detection Based on Satellite image	61.34% 97.4%	detection system Improve the accuracy of identification while maintaining good detection efficacy. Intensive transfer- learning is implemented to improve accuracy of identification.	performance and make the system more resilient. More Convolution Networks can be called to improve the performance of the design features built into the deep network. Detection efficiency is far from acceptable relative to the results of detection on everyday images
[60]	Car detection/ 2018 Car detection/ 2019	YOLOv2, k-means algorithm, Hard Negative Mining deep learning, Detection tuning yolov3 network, deep neural network, Sample Expanding for the Intensive Transfer Learning	Video based detection Based on Satellite image	61.34% 97.4%	detection system Improve the accuracy of identification while maintaining good detection efficacy. Intensive transfer- learning is implemented to improve accuracy of identification.	performance and make the system more resilient. More Convolution Networks can be called to improve the performance of the design features built into the deep network. Detection efficiency is far from acceptable relative to the results of detection on everyday images Inspired by the
[60]	Car detection/ 2018 Car detection/ 2019	YOLOv2, k-means algorithm, Hard Negative Mining deep learning, Detection tuning yolov3 network, deep neural network, Sample Expanding for the Intensive Transfer Learning	Video based detection Based on Satellite image	61.34% 97.4%	detection system Improve the accuracy of identification while maintaining good detection efficacy. Intensive transfer- learning is implemented to improve accuracy of identification.	performance and make the system more resilient. More Convolution Networks can be called to improve the performance of the design features built into the deep network. Detection efficiency is far from acceptable relative to the results of detection on everyday images Inspired by the positive effects of

2.7 Road Blocker Detection

After implementation of the detection of the road blocker on the road, Autonomous vehicles has capability to survive with road blocker when hydraulic road blocker rapidly displayed at a very short distance, and the accidents of autonomous vehicles must be overcome. In addition, detection of road blocker will provide safety to the vehicle and its passenger. Road blocker detection and distance calculation algorithm increased navigation system on autonomous vehicle because of their visibility during driving scenario. Detection of road blocker is great inventory on navigation system of autonomous vehicle also, it gives us acceptable result which is more accurate as compare to other navigation systems in autonomous vehicle (Farhat, 2020).

S.NO	Work on	Methodology	Parameter	Result	Advantage	Disadvantage	
			Obtained				
[62]	Road	Color	Color	97%	Autonomous vehicles	Future research will focus on	
[63]	blocker	Detection,	Based		have capability to survive	expanding existing methods of	
	detection	SVM, KNN,			with road blocker when	identifying certain modes of	
	/2020	Naïve Bayes,			displayed at a very short	transportation.	
		Decision tree			distance		

Table 7:Road Blocker Navigation system for Autonomous Vehicle

Numerous studies have been conducted on issues related to the detection of signs, traffic lights, etc. The existing navigation framework is limited, which has motivated many scholars to improve the navigation performance, detection and recognition of the ADAS navigation system in complex situations. Table 5.6 shows past navigation system of autonomous vehicle in driving scenario.

S.No	Navigation	Dataset		H	lighest /	Accurac	y Achived	
1.	Traffic light	8				ii T		99%
2.	Traffic sign	STOP			Ĩ	T		99.01%
3,	Pedestrian	A.				T T	I	96%
4.	Car	◒▰						99%
5.	Traffic lane	¬ t ₽-	-		16			99%
6.	Traffic cone			- 11 	1	- 11 - 11	85%	
7.	Road Blocker			T'		4		97%

Figure 2: Highest Accuracy Achieved in Different Navigation System

3. Conclusion

Although the existence navigation system will be needed more enhancement for fully autonomous vehicles. Traffic cone, pedestrian, road sign, road lane, road blocker, road cone in potential smart cities, Detection and recognition remains an important issue for research groups. Because of the high demands in terms of reliability, designing a vision-based system is a

huge development task, even for the simplest applications. Several functional elements are needed for a stable system, and the recognition and handling of many different conditions and assumptions. Moreover, a great testing effort is required, as many of the cases of failure are rare and difficult to forecast. The high difficulty of the infrastructure and the great development work required to build effective networks greatly hinder the knowledge of roads through research and development. Based on this review, driver intention inference is believed an important function for ADAS and intelligent vehicles, which is able to reduce the conflicts between the driver and the intelligent vehicle. Understanding of human intention also enables a better design of the decision-making algorithms for automated vehicles. In this article we have analyzed the major recent developments reported from 2017 onwards in this field of science, outlining specific phases of most approaches. Future scope in this area includes introducing more efficient techniques for road sign, road lane, cone, traffic light, car, and pedestrian, text detection and recognition to move from one place to another Also, the existing methods in autonomous vehicle does not provide any attention to the road blocker to detect the road blocker and find distance between road blocker and vehicle.

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