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Obstacle Detection Challenges of Camera Sensor Designed for ADAS

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Abstract*: Camera is a very crucial sensor for ADAS which is commonly used in all the vehicles to assist driver by providing information about all the obstacles around the vehicle during a drive. The Camera sensor is a vision based sensor and it is highly preferred because of its advantages like excellent in classification, good resolution, very economical and small in size. Still this sensor is having some disadvantages like huge computational load, failed to detect obstacles due to poor light and weather conditions and even less capable to estimate the distance from the obstacle. In recent years so many research works were performed to overcome these challenges, for making the camera a robust sensor. In this paper, the challenges in detection faced by camera sensor were focused and their respective solution is discussed, which are required to improve the effectiveness in vision based detection.

***Keywords*: ADAS, Camera Sensor, Challenges, Vision based detection.**

I. INTRODUCTION

In India on road vehicles count is increasing day by day and due to this there were a lot of traffic jams and also accidents were occurring. Now-a-days ADAS is getting installed in all the vehicles, for the sake of providing a perfect infotainment to driver about all the obstacles which are in the travelling path to avoid collisions. In general while travelling on the roads, driver will come up with so many obstacles in his path which could be in motion or in static. In so many cases driver fails to notice these obstacles and getting prone to accidents. The reasons were like due to vulnerable road users and also some blind spots in driver vision created by the vehicle structural design itself. In this case there should be a system which is able to detect, if necessary predict the obstacle and should warn the driver in case if any collision risk detected. The ADAS can be made up of different sensors like mainly Camera, Lidar, Radar and GPS based upon the functional requirements. The most commonly preferred sensor, which is satisfying the above requirements for the ADAS system is Camera which is a vision based detection system.

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This sensor is similar to the human vision which can detect the color, texture and other information's by classifying an obstacle perfectly. The main advantages of camera are good resolution, excellent classification of detected obstacle, small in size and very cheap which are making it a robust sensor for the ADAS. The camera sensor usually includes three phase initially capturing the image of environment, an input phase; later computing, classifying and detecting the obstacles which is the convolution phase and final phase is creating an output image with the obstacle and drivable area detection which is the output phase. Initially the CNN algorithm need to be trained efficiently with different datasets which contains data about different obstacles. The accuracy in detection mainly depends on this training phase itself. The Camera assisting areas and the object detection process is represented in the below Fig. 1 and Fig. 2.

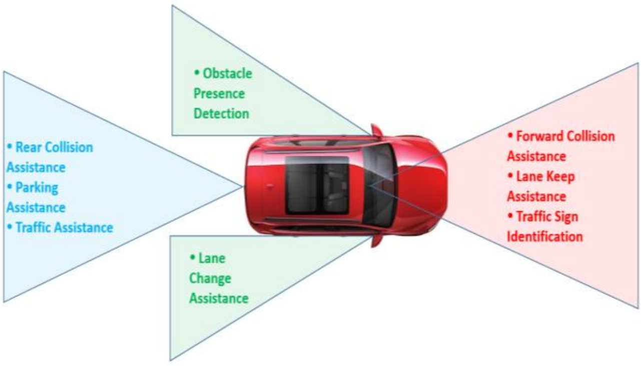

Fig. 1. Camera Assisting Areas during a Drive.

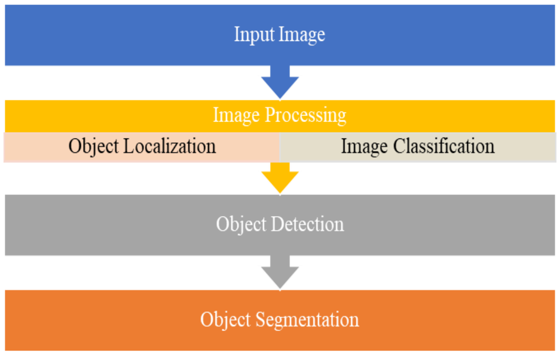

Fig. 2. Object Detection Process of Camera Sensor

The main challenges faced by this sensor in this process are, initially providing a perfect input to the convolution network irrespective of environmental conditions, As the weather conditions like rain or fog, sunny day illumination changes and night time absence of light where effecting the camera vision in capturing the data. And later on effecting detection process.

The second one is Huge computational load, as it include some sequence of repeated operation where the input image will be filtered out with different trained data set it includes so many arithmetic and decision making operations like SVM, LSTM, IPM etc… were computationally heavy. Due to this reason there is a requirement of high end hardware setup. Another challenge is to provide the output within less time, i.e. while driving, ADAS need to give collision alerts in a quick way, and delay in this process will lead to severe damage.

The vision based detection system is also facing so many challenges in the estimation of collision distance estimation. In this paper an in-depth research work was performed mainly targeting the challenges in the detection and summarized the solution.

II. DIFFERENT ALGORITHMS FOR VISION BASED OBJECT DETECTION

Deep Convolution Neural Networks (CNN) are most commonly used algorithms for the image classification. The CNN will be having two phases which are the training and inference phase. In the training phase so much data will be loaded and filter data sets will be created. These filter data sets will be used for the Inference phase. The Inference phase is the real time image classification phase where it will take an input which is an image and tries to identify the objects in the image by processing the image through the hidden layers and gives an output image by identifying all the objects in it. So finally there will be three main layers in the inference phase which are the Input Layer, Hidden Layer and Output Layer. The D-CNN architecture is shown in Fig. 3.

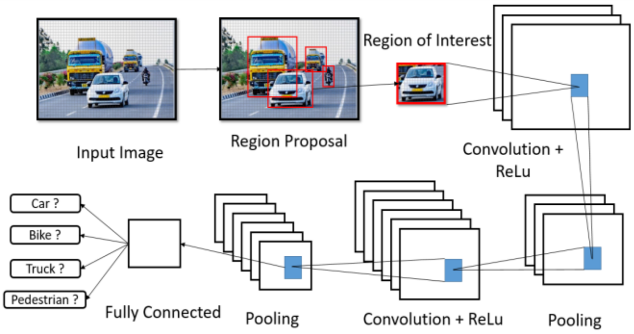

Fig. 3. D-CNN Architecture for Object Detection.

The Hidden Layer is the most import place where the classification process will be performed and it have four sub layers within it and they are convolution layers, ReLU (Rectified Linear Unit) layers, Pooling Layers and Fully Connected Layers. Initially in the convolution layer which is core part of the CNN, the image features like edges, colors will be extracted with the help of filters/kernels loaded beforehand and this convolution is a linear function. ReLU is a non-linear activation layer which is added to the convolution layer. This ReLU is a non-linear function which will tries to understand the non-linearity in the surroundings. Later the output will be processed into the pooling layer which is another type of non-linear function where the output of the convolution layer will be down sampled which helps to reduce the complexity in computation and memory. In the fully connected layer finally detects the output and prepares some bunch of output data's and with the help of probability distribution algorithms like SVM it decides the best of the outputs. This fully connected operation is a very computational and requires more data for performing the operation. Initially this phase of Image Classification with CNN is named as Regional CNN (R-CNN) [41]. In this at the start it tries to identify the region proposals for CNN with a selective search and then process into the CNN and achieves an output of labelled images having a bounding box around it. Later to reduce the box size according to the object size it uses a simple linear regression model. Later R-CNN is updated to Fast R-CNN [42] were all the CNN architecture phase, classification and regression phase were created as a single network. Here the pooling phase was also included into the convolution phase and tries to reduce the iteration process in between these phases. The Fast R-CNN again modified into a new version which is named as Faster R-CNN [45] where the initial regional proposal phase is speeded up, for this the first iteration result of CNN were made as a feedback for the second iteration regional proposal phase. Later semantic segmentation phase was also included as later on phase of CNN and it is called as Mask R-CNN [29]. In this methodology the image is classified as per the Faster R-CNN architecture but later a pixel level semantic segmentation is also performed which is very advantageous in the process of Image classification with high accuracy and it was also helpful for color labelling. So when discussing about the better regional proposal system **Jungme Park, Sriram Jayachandran Raguraman, Aakif Aslam, Shruti Gotadki [36]** proposed an advanced Regional Proposal Mechanism (RPM), which not only works with the existing trained data but also considers a continuously trained data from the images captured with the help of a jointly learning architecture. This methodology improved the performance of region proposal and also reduced the computational time. **K. Zebbara, M. El Ansari, A. Mazoul, H. Oudani [28]** proposed a very simple method for defining region of interest in a quick and accurate way from images, by extracting the edges and calculating symmetry to build the region box around the obstacles.

In order to reduce the computational load **K. Ismail, T. Breckon [27]** elucidated the functionality of Extended Faster R-CNN in the urban scenario and its accuracy in detection and also capable in the estimation of attributes, but it is having very less accurate in color labelling. This can be used as an alternative for the Mask R-CNN when there is a requirement of less computational load during segmentation process. **H. Han, Y. Chen, P. Hsiao, L. Fu [17]** proposed a semantic segmentation approach with Efficient Neural Network (Edgenet) alternative way for Traditional DCNN. This method might not be as perfect as the traditional way but it has increased the computation speed greatly. **Xiangyong Liu, Guang Chen [33]** proposed the k-means and improved k-means methodology for the semantic segmentation process which are having a great computational efficiency and also improved k-means proved more accurate in semantic segmentation process compared to k-means. Still it is not that much accurate when compared to traditional DCNN and even more it cannot label the classified objects. **X. Liu, H. Wang [52]** proposed a fusion methodology of object detection and limited semantic segmentation for reducing the computational load on the hardware system where there will limited requirement of color labelling.

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Demonstrated the fusion methodology real time for lane semantic segmentation and Vehicle detection. Finally it can be observed that the only way to reduce the computational load is by optimizing the performance of detection. To increase detection accuracy **Vinh Quang Dinh, Farzeen Munir, Shoaib Azam, Kin-Choong Yow, Moongu Jeon [47]** developed a new methodology for better accurate vehicle detection where initially with the help of transfer learning vehicles were detected from two focal length images and processed with the help of Faster R-CNN architecture.
This had doubled the detection accuracy when compared with Faster R-CNN alone. **J. K. Suhr, H. G. Jung [21]** proposed a way of representation in final classification of detected objects with the help of Stixels for Faster R-CNN architecture which will eliminate the difficulty faced by bounding boxes method in the classification of vegetation, walls like classes. There is also a better chances to increase the detection accuracy by continuously training the system from the output data as mentioned by **Pedram Fekri, Mehrdad Zadeh, Javad Dargahi [15]** proposed a recurrent neural network approach to create a trained data continuously from the output of DCNN in order to reduce the effort for training the data and also increase the accuracy in classification of object classes. **Wenwen Zhang, Kunfeng Wang, Yating Liu, Yue Lu, Fei-Yue Wang [50]** proposed a similar methodology named as scene specific detection where creation of a trained data set done from the detected images output. This methodology was performed with a static camera, for an increased accuracy in pedestrian detection.

III. CHALLENGES FACED IN OBSTACLE DETECTION

The Obstacle detection with camera is identified as a better way to classify and detect the obstacles. This accuracy can be effected by different aspects, like illumination effects, night time, bad weather, huge occlusions, etc… the estimation of collision distance is also a big challenge with camera detection. So regarding to this research work is done to find solutions to these challenges. The real time obstacle detection with camera can be seen in Fig. 4.

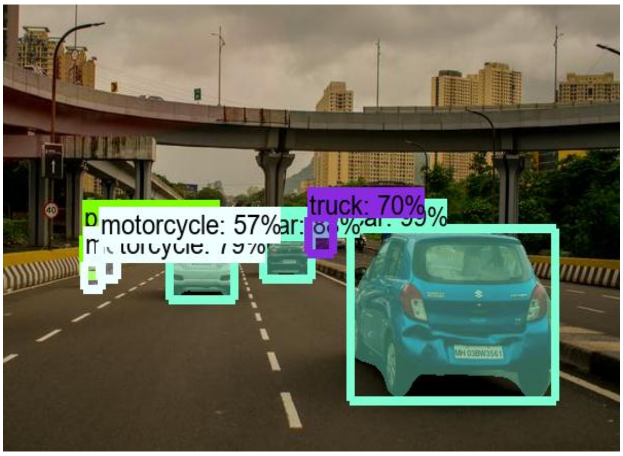

Fig. 4. Real Time Object Detection and Instance Segmentation.

A. Illumination Changes

In the vision there will be illumination effect which is caused by light. The computer vision faces so many difficulties in the process of object detection due to illumination. This is due to not having sufficient trained data sets in different illumination levels, but it is also difficult to prepare such a trained data set. To overcome the detection challenges with illumination changes, **L. Ray, M. Kulkarni [30]** elucidated a method which can adjust the dynamic whiteness levels. This method usually detects the road and collects the road image RGB as feedback and if any disturbance is found in these values the network will automatically try to adjust the brightness levels in the image which will reduce the illumination effect in detection. **Xing Wu, Chao Sun, Ting Zou, Linhui Li, Longjun Wang, Hui Liu [54]** had prepared a small prototype which can detect three types of illumination levels (i.e. low, medium and high) in the real time scenario and accordingly with the help of SVM the algorithm will change the illumination levels in the captured data. **Chengyang Li, Dan Song, Ruofeng Tong, Min Tang [10]** stated an illumination aware weighting mechanism in the Faster R-CNN algorithm which will first identify the illumination level and later try to adjust levels of the vision and tries to detect the pedestrian.

B. Background Complexity

In so many places, computer vision is facing lot of difficulty to differentiate the obstacle from the other environment which could lead to reduce in accuracy or lack of detection of obstacles in those conditions.I n the situation of detection of obstacle from an image with huge background complexity, **W. Zhang, L. Tian, C. Li and H. Li [48]** demonstrated a methodology to detect pedestrians individually from the crowd with the help of SSD, i.e. initially by separating crowd from the background and later by changing the kernel filter sizes. **Wei Tang, Zhijian Wang, Jiyou Zhai, Zhangjing Yang [49]** demonstrated a saliency detection of the human in the farm where there is a huge background complexity. Initially the image is partitioned with super pixels and the background, foreground connectivity is identified with in the image. Later with the help of markov graph by calling both the cases, segmentation process is performed. **Yingjun Jiang, JianxinWang, Yixiong Liang, Jiazhi Xia [23]** elucidated the method of pedestrian detection in both the static and dynamic cases with the help of space optical flow. This method has shown an increase in accuracy in the case complex background situations.

C. Shadows

Shadows are one of the most important constraint which are misleading the computer vision in a wrong way. This will lead to wrong detection and unnecessary alerts which may panic driver. This could sometimes leads to accidents.

To identify and differentiate shadows from the image detection process, **Felix Naser [13]** proposed an extension algorithm named shadowcam which will help to identify shadows and also the changes in illumination later adjust everything and tries give a clear output.

S. Mohajerani, P. Saeedi [44] proposed a method to detect shadows alone with the existing CNN methods by identifying the change in color contrast in the computer vision images. Later the detected image will be used for the trained data set to increase the accuracy.

Hang Shi, Chengjun Liu [19] elucidated the shadow detection method from a video of static traffic surveillance cam with the help of Gaussian Foreground modelling and Gaussian mixture model algorithms. But this method is efficient only static cameras.

D. Occlusions

The computer vision will have good detection accuracy only of the vehicle which is in front of it, but there will be some other vehicles which will be travelling in front of those vehicles and get partially blocked in the sight of computer vision.

This occlusion will create a constraint of not assisting the driver with proper detection. This may cause difficulties during overtakes or turnings. To accurately detect obstacles in the case of occlusions, **Pedram Fekri, Mehrdad Zadeh, Javad Dargahi [15]** demonstrated the vehicle detection during occlusion based on the vehicles previous detection with the help of LSTM network combined with the Faster R-CNN network. **Charan D. Prakash, Farshad Akhbari, Lina J. Karam [9]** demonstrated the inverse prospective mapping methodology and converted the normal image into bird eye view image. Later continued the object detection process which had shown a good improvement in detection accuracy. **Lei Wang, Xiaoyun Fan, Jiahao Chen, Jun Cheng, Jun Tan, Xiaoliang Ma [31]** proposed a sparse convolution method and voxelization to convert the 2D image into 3D space in cloud point for the better detection of vehicles which are covered with other vehicles.

E. Night Time

The major challenge faced by obstacle detection is detection during night time. It is very difficult to prepare a perfect trained data set of night time, so maximum trained data set which is available were trained during the day time. Due to this it is becoming very difficult to identify obstacles with the automotive headlamps and other artificial lights present in environment. In order to increase the night vision detection accuracy, **Yaoyang Mo, Guoqiang Han, Huaidong Zhang, Xuemiao Xu, Wei Qu [56]** elucidated a method to detect the vehicles in night time by identifying the vehicle headlights and performing semantic segmentation according to it. Later this will be combined with the general CNN architecture detection process to increase the accuracy in the vehicle detection. **Jong Hyun Kim, Ganbayar Batchuluun, Kang Ryoung Park [25]** proposed a visible light camera usage for the detection of pedestrians during night time with the CNN architectures. Later to increase the accuracy the detected frames where reused for training the data sets. **Sharath Yadav D H, Asadullah Ansari [11]** elucidated how the vehicles used to detect during night time with the head lamps and later proposed a predictive analysis for the detection during an illumination effect caused by the opposite vehicle. This methodology will reduce the effect of blind attacks during night vision. **Rajaram Bhagavathula, Ron Gibbons [5]** elucidated a method to identify real obstacle during night time without the effect of luminescence i.e. by training an algorithm to identify and differentiate the positive and negative contrasts to reduce the wrong detection rate.

F. Different Weather Conditions

Generally the vision will get blocked sometimes due to the water droplets this is most commonly seen in the rainy season and also in winter season due to mist. It is very difficult to perform object detection process with the images captured in these scenarios. Regarding to the task of obstacle detection during bad weather conditions, **Mazin Hnewa, Hayder Radha [20]** proposed a deraining algorithm with respect to the rain intensities, where the obtained image will be sent through this algorithm to identify the water droplets and try to give out a clear footage which can processed through CNN for detection. **Yazan Hamzeh, Zaid El-Shair, Samir A. Rawashdeh [18]** demonstrated with different trained data sets and compared the clear image and image taken during the raining time, concluded that the efficiently trained data set is necessary for a robust detection and later finalized that YOLO dataset as good at object detection even during the rainy time when compared with other sets. **Yugang Wang, Ting-Zhu Huang, Xi-Le Zhao, Tai-Xiang Jiang [58]** proposed a video streak rain removal with the help of tensors such that it can remove the rain streak in the images or video and can perform general object detection process which had been found effective. **Rania Rebai Boukhriss, Emna Fendri, Mohamed Hammami [40]** proposed a methodology of continuously changing spectra with respect to illumination changes due to bad weather conditions like fog and rain, this will help to detect moving objects with better accuracy.

G. Distance

Measuring the distance between the obstacle and the vehicle will give a clear cut information to driver regarding the collision awareness and helps him to take a good thought to avoid it. This will be useful during traffic jams and parking scenarios. Still it is very difficult task to identify distance with the help of a camera sensor. Estimation of distance with computer vision is possible and regarding to this, **Alexander A S Gunawan, Deasy Aprilia Tanjung, Fergyanto E. Gunawan [3]** considered a static cam and observed the vehicle position at each frame which are passing under the cam, later with the help of direct linear transformation vehicle speed and distance were evaluated. **Pedram Fekri, Vajiheh Abedi, Javad Dargahi, Mehrdad Zadeh [14]** had trained a data from the recorded images pixel to estimate the distance between the front vehicle rear end and the camera sensor. In a simulation environment a test run is performed and tried to evaluate the acceleration and estimated the collision rate of the vehicle. **Jian Zhong, Xinbo Chen, Yibing Peng, and Yan Li [61]** elucidated a methodology to estimate the distance between the camera and front vehicle by identifying the pixels size of the vehicles license plate. Initially the license plate position is localized and later based upon the change in license plate size the distance was estimated. It is tested only at very low speeds.

H. Area of Vision and Range

The area and range of vision is very important to alert the driver about surrounding obstacles on the way, but the computer vision doesn't have a long range of vision and the area of vision is also limited to an angle.

During Lane changes or turnings or in some other cases the vehicle will fail to detect the obstacles which are not in its vision, these can be treated as blind spot during motion.

To increase the obstacle detection capability to long range by overcoming the detection accuracy errors, **Qing Li, Tao He, Guodong Fu [38]** conducted tests and identified that with the computer vision there is always small error recorded when compared with the real time position and detected position of the obstacle and concluded that the error could be more when the vehicle is at a long distance. **Vinh Quang Dinh, Farzeen Munir, Shoaib Azam, Kin-Choong Yow, Moongu Jeon [47]** performed an experiment by taking two cameras at different focal lengths and successfully detected obstacles at a long range with higher accuracy.

Souvik Bose, Ashwani Kumar Singh, D V Ram Kumar Singampalli, Chandraprakash lalwani [7] elucidated the obstacle detection by considering three cameras along the front end of the car to increase the area of vision which is the only option. **Jian Wu, Sihan Liu, Rui He, Bohua Sun [51]** elucidated a trajectory prediction methodology with the help of GMM and tried to predict the other vehicles path, which could assist during the lane change to avoid collision with the vehicle even if it is out of the vision area.

IV. OTHER TYPES OF VISION BASED DETECTION SENSORS

A. Stereo Vision Camera

Stereo vision camera is an assembly sensor which includes two monocular cameras placed along same axis in parallel with a distance indirectly represents the Human Vision system. This sensor is having a major advantage of creating a 3D View of the environment from the two 2D view images. This advantage is making stereo vision system more preferable when compared to Monocular camera. The stereo vision FOV and its working process can be seen in below Fig. 5 and Fig. 6.

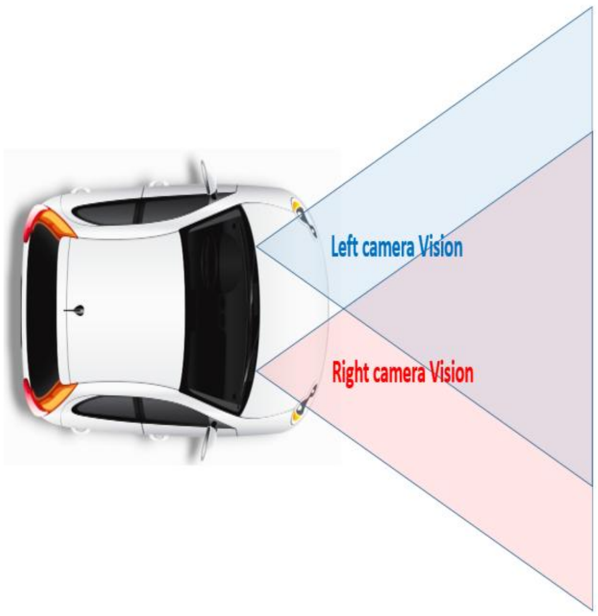

Fig. 5. FOV of Stereo Vision Camera.

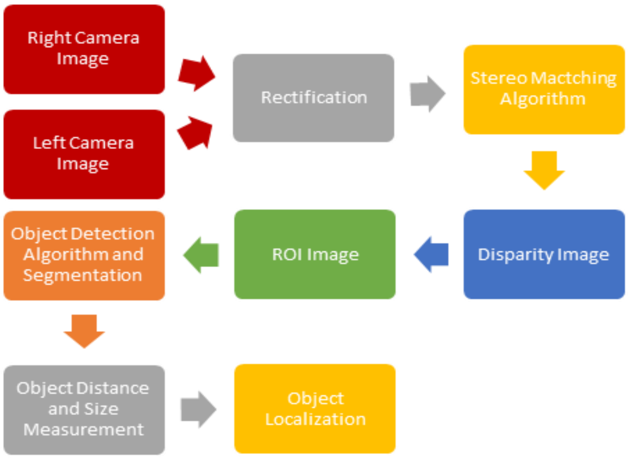

Fig. 6. Object Detection and Localization Process of Stereo Vision Camera.

The capabilities of stereo vision is discussed where, **Abdelmoghit Zaarane, Ibtissam Slimani, Wahban Al Okaishi, Issam Atouf, Abdellatif Hamdoun [2]** elucidated the process of real time distance measurement between the camera and it's in front vehicle. The methodology is demonstrated in static conditions and it has given a good accurate results compared to the actual measured distance. **Carlos Guindel, David Martín, José María Armingol [8]** elucidated the working of stereo vision system by image collection from two individual cams, converting images into bird eye view and later construction of 3D spatial view by combining both the images. The object detection is performed with the help of CNN architecture. **P. Huang, H. Lin [35]** elucidated the Stixels generation algorithm for the Stereo vision system for the collision detection at rear end of the vehicle.

B. IR Camera

Infrared camera or Thermal imaging camera or Night Vision camera is one of the camera sensor equipped with IR which uses infrared radiation to detect obstacle in its paths. As mentioned this sensor detects the obstacles based upon their heat. This sensor gives thermal image as output. So for working with this type of camera sensor requires a special Thermal images data set to detect the obstacles from thermal images Research had been done to develop the capabilities of detection with IR vision, regarding to this, **Qing Kang, Hongdong Zhao, Dongxu Yang, Hafiz Shehzad Ahmed, Juncheng Ma [37]** described the way of IR vision object detection with the help of different CNN networks and Later compared different convolution network architectures and also compared the results of normal camera detection and IR camera detection. **J. Kim [22]** with the help of inverse perspective transformation elucidated the method of pedestrian detection and distance measurement with the Thermal vision camera. The distance measurement is not that much accurate but the measuring accuracy can be improved. **Xiaobiao Dai, Yuxia Duan, Junping Hu, Shicai Liu, Caiqi Hu, Yunze He [53]** performed the pedestrian detection during Night time with Infrared camera and compared the results with the general vision, SWIR and LWIR in different aspects. **Aparna, Yukti Bhatia, Rachna Rai, Varun Gupta, Naveen Aggarwal, Aparna Akula [1]** elucidated the methodology for the detection of pot holes with the help thermal vision camera. The detection has been tested in three cases i.e. potholes during day time, pot holes during night time and filled potholes. The algorithm had efficiently detected the potholes all the time.

C. IR Camera Fused with Monocular Camera

The detection of obstacle alone with IR vision is having some issues in the process of classification and colour identification. So regarding to this the fusion method is proposed where the IR vision is fused with the Monocular camera and regarding to this **Chengyang Li, Dan Song, Ruofeng Tong, Min Tang [10]** has designed a multi spectral detection system based on the combination of thermal and normal image detections. In this paper it was concentrated only on increasing the detection of pedestrians with the help of Faster R-CNN network. **Rania Rebai Boukhriss, Emna Fendri, Mohamed Hammami [40]** developed a method for the detection of moving obstacles in all types of illumination levels including day and night times with the help of combined IR spectrum and VIS spectrum image data. Y.

Chen, H. Xie, H. Shin [55] developed a multi-layer fusion method in the combination monocular and thermal cameras for the accurate detection of pedestrian during different illumination conditions and an 11.35% increase in accuracy has been found when compared to general Faster R-CNN detection.

D. IR Stereo Vision Camera

IR Stereo vision camera is a sensor which replicates Stereo Camera made up of IR cameras which is having the combined advantages of stereo vision and thermal imaging.

The advantages of the IR stereo vision camera is elucidated by **Yi-chao Chen, Fu-Yu Huang, Bing-Qi Liu, Shuai Zhang, Ziang Wang, Bin Zhao [57]** demonstrated a stereo vision system with LWIR and increased field of vision for the detection of pedestrians. The system was having a 92.5% detection rate in different background complex scenes. Also within a range of below 30 m the distance has been estimated very accurately with a negotiable error. **Ziang Wang, Bingqi Liu, Fuyu Huang, Yichao Chen, Shuai Zhang, Yue Cheng [62]** elucidated the methodology and construction of an ultra-wide LWIR stereo vision sensor for robust detection of obstacles during all scenes. Also explained the calibration process for both monocular and stereo thermal vision camera for distance measurement.

V. FUSION WITH OTHER TYPES OF SENSORS

There are some other sensors like LIDAR and RADAR which are also being used for the obstacle detection. But each and every sensor is were some disadvantage which are restricting their 100% performance in detection. For example camera is good at classifying the obstacles but it is ineffective in bad weather conditions. Similarly the LIDAR is good at detecting obstacle at long range and localizing them but it is very costly and it is not good classifying the obstacles. Radar is very effective in detecting obstacles in bad weather conditions and it is cheap when compared to LIDAR but it is not that much efficient as LIDAR. In this case, Fusion of Multiple sensor will give rise to better Obstacle detections. The main pros and cons can be seen in below Fig. 7.

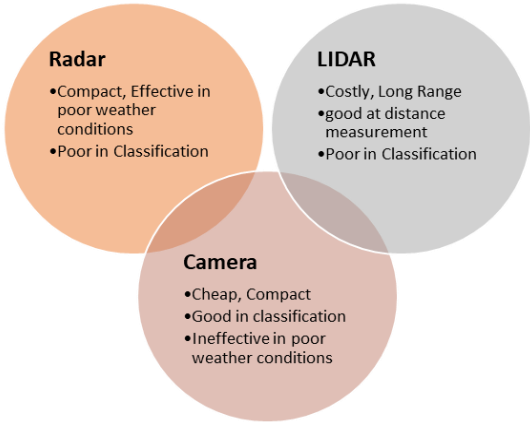

Fig. 7. Pros and Cons of Different ADAS Sensors.

A. Fused with LIDAR

LIDAR is a light detection and ranging device which is mainly used to measure the distance with the help of laser light illumination and by capturing its reflection. It is having capability to gather obstacle data around 360^0 of the vehicle. It is very accurate in representing the 3D world even by identifying small objects which makes it a robust sensor for the obstacle detection. Regarding to this **Lalitha Dabbiru, Chris Goodin, Nicklaus Scherrer, Daniel Carruth [12]** demonstrated the obstacle detection by LIDAR and semantic segmentation with the help of Squeeze Seg CNN. In this the detection and segmentation accuracy of different classes were compared in between the 8-beam and 16-beam LIDAR systems in which the 16-beam had shown a little bit improvement in the detection accuracy. The whole system was tested at a slow motion of 21 mph.

Even though LIDAR alone is sufficient to detect and classify most of the obstacles, still there were so many cases where structural ambiguity and occlusions had effected there detection accuracy, which mislead driver in different scenarios. Due to this reason a Robust LIDAR and Camera fusion sensor with different types of fusion techniques (like early, middle, late) were used to overcome the detection issues.

The fusion methodology requires additional algorithm, regarding to this **Zheng Gong, Haojia Lin, Dedong Zhang, Zhipeng Luo, John Zelek, Yiping Chen [60]** explained a framework for creating the fusion of 3D LIDAR and stereo vision data were a better object detection in 3D point cloud is possible by eliminating the structural ambiguity with the help of a mobile and backpack laser scanning systems. The methodology was tested by mounting the backpack on person equipped with camera and LIDAR sensors where LIDAR sensors used to build 3D map in cloud and camera is used for the vision based object detection. **Luca Caltagirone, Mauro Bellone, Lennart Svensson, Mattias Wahde [34]** explained about the issues in LIDAR 3D semantic mapping and proposed a fully convolution neural network to combine the LIDAR point cloud data and camera image data for the prefect road detection and segmentation. Also instead of traditional early and late fusion, here a cross fusion methodology is used to limit the drawbacks and to improve the object mapping and detection accuracy. **Jing Li, Xin Zhang, Jiehao Li, Yanyu Liu, Junzheng Wang [24]** constructed a robot and equipped it with the LIDAR and camera. The LIDAR is having an issue of imperfect 3D semantic mapping and visualization of environment while moving, for this reason a the sensor is fused with the camera such that the image segmentation results were fused with the point cloud map and the LIDAR mapping accuracy is increased.

B. Fused with RADAR

RADAR is another most common sensor used in vehicles for the detection of obstacles with the help of radio waves. **Vivek Bithar, Aditya Karumanchi [6]** explained how the radars can be used to detect obstacles and help the driver to prevent collision during lane change by calibrating the distance from other vehicles. When compared to LIDAR these are cheap and comparatively efficient. There are three types of radars based upon the range i.e. long range, medium range and short range radars. But still Radars sensors were not that much capable to classify the obstacles and also fail to detect small size obstacle. Due to this reason a Fusion system with camera is most used and regarding to this **Jungme Park, Sriram Jayachandran Raguraman, Aakif Aslam, Shruti Gotadki [36]** proposed a fusion sensor with the combination of camera and radar to overcome the individual limitations. The algorithm initially detects the objects with the radar and gives those coordinates to the camera input where the DCNN fuses both the radar and camera data and tries to detect the vehicles at long range and measures the distance. **Jie Bai, Sen Li, Jinzhu Wang, Libo Huang, Lianfei Dong [4**] proposed a fusion system by combing the distance measuring capability of radar and object detection by Camera sensor. The K-mean algorithm is used for the clustering of detected data. This methodology has proven its accuracy in detecting the road boundary conditions and drivable area for a long range. **Darui Zhang, Ning Bian, Daihan Wang, Hang Yang, Xinjuan Tuo [59]** observed the error in distance measurement with the help of radar and camera fused system and for that, proposed a weighted distance calculation method where the weight factors will be evaluated from both the sensors individual detection data and it has proven its accuracy better than the traditional Euclidean measurement method

C. Global Positioning System

Global positioning system (G.P.S) can be used for assisting in the detection of other obstacles which are holding a GPS unit. The GPS connectivity between the vehicles will help to maintain contact in between the vehicles such that they can exchange speed, moving direction and so many other parameters data in between them which is helpful to avoid collisions. **Xuanhe Li, Jian Wu, Rui He, Bing Zhu, Jian Zhao, Hang Zhou [32]** developed a vehicle to everything system in an simulation environment where cars had been interconnected with the GPS communication system and will exchange there motion related data, such that they can avoid collision during turning and or in other situations where there will be sudden speed change or any other cause of collision. **R. Otani, A. Shikishima, T. Wada [39]** used the GPS system to establish a communication between the vehicle and pedestrian. With this system the network will be able to track the pedestrian movements and will be able to alert the drive to change the path according to it.

The Drawback of the GPS sensor is it will not be available in remote areas and also if the other object is having any issue with the GPS or not having GPS, then this system won't be able to recognize the obstacle which cause severe accident. Due to this reason GPS system can only be used as a secondary assistance to the primary sensor detection data which could be camera, LIDAR, Radar etc. Finally based upon above survey all the different sensor were compared according to their parameters related to the Obstacle detection like range, classification, cost effects of weather etc… and were listed in the Table I.

Table- I: comparison of parameters related to detection of various adas sensors.

Type of Sensor	Range	Shape of Object	Classification	Distance and speed estimation	Effect of Illumination Changes	Effect of Poor Weather	Shadows Effect	Night Vision	Cost
Monocular camera (traditional algorithms)	Moderate	Good	Excellent	Not capable	High	High	Yes	Bad	₹₹
Monocular camera (improvised algorithm)	Moderate	Excellent	Excellent	Moderate	Medium	Medium	Varies	Moderate	₹₹
Stereo vision camera	Moderate	Excellent	Excellent	Good	High	High	Yes	Bad	₹₹₹
IR camera	Moderate	Good	Excellent	Not capable	Low	Low	No	Excellent	₹₹₹
IR stereo vision camera	Moderate	Excellent	Excellent	Good	Low	Low	No	Excellent	₹₹₹
Monocular camera with IR camera	Moderate	Excellent	Excellent	Not capable	Low	Low	No	Excellent	₹₹₹
Fusion of LIDAR and monocular camera	Excellent	Excellent	Excellent	Excellent	Low	Medium	No	Excellent	₹₹₹₹₹
Fusion of Radar and monocular camera.	Excellent	Excellent	Excellent	Excellent	Low	Low	No	Excellent	₹₹₹₹

VI. CONCLUSION

In this paper different challenges faced by the camera sensor in detection were identified and their respective solutions are discussed. It is found that relentless training of the algorithm with the output data will help to improve the accuracy in detection. The computational load can be reduced by optimizing the detection requirements. The camera can be made capable for estimating the collision distance either with the improved algorithms or with usage of other types of fused camera sensors based upon the necessity. The camera detection accuracy during night time and under different weather conditions can be improvised with the help fusing the monocular camera with an IR camera and also there were some deraining and contrast control algorithms which can eliminate other sensor necessity. Fused sensors are giving a great detection accuracy in all cases, but it is also increasing the cost of sensor for ADAS. Finally it can be concluded that monocular camera alone with the improvised algorithm will be sufficient for ADAS system in order to assist driver about collisions.

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