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An Experimental Assessment of Deep Learning on Highway Driving

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Abstract: *Many groups have used a different types of deep learning techniques on computer vision in highway drivingscenes.duringthispaper,we'llobservetheexperimentalassessmentofdeeplearning.Computer Vision with deep learning can bring a reasonable and robust, yet a powerful solution to the sector of autonomous driving. To prepare the deep learning for practical applications the neural networks requires the data sets to train for all types of scenarios of driving. We collect the Data sets and train the model with deep learning and computer vision algorithms for recognition of cars and lanes.*

***Key Word**: learning, computer vision, autonomous driving, neural networks.*

I. INTRODUCTION

Since the DARPA Grand challenges there was visible a exponential boom in software and studies of self-riding cars. A self-driving automobile on an city street and motorway are absolutely contrary ends of a line as highways are nicely marked and maintained. Today's self-driving cars are equipped with high cost precision sensors and technologies like LIDAR[4] radar, sonar, high accuracy GPS and detailed maps. Cameras give a greater features thanradarandsonar.Whilethecostofcamerasisafractionoftheseprecision sensorsandtechnologies.With the advancement of computer visioning we can use cameras as reliable redundant sensors for autonomousdriving.

Computer vision is a subset of main stream AI which deals with the field trains computers to learn and understand the visual world around us through the use of camera and video images and deep learning algorithms that enable machines to accurately identify and classify objects. Whereas Deep Learning is a subset of machine learning in AIthathasnetworkcapableoflearningunsupervisedorunstructureddatawiththeneuralnetworks.Deeplearning is a data center that requires extensive computation but minimal management engineering. In recent years, computing capacities have increased, helping to enhance deep learning and be successful in supervised tasks. A neural network is a set of algorithms that attempt to detect a relationship in a data set through a process that works the way the human brain works. A neural network, that trains for days and also weeks on big data sets is capable to interface in real time with the model sizes which are not more than hundreds MB. [2].

By using the current expensive sensors such as LIDAR and mm-GPS and with the use of cameras we create a proper video data set which has labeled lane marking and annoted the vehicle positions with their relative speed canbeusedtobuildalabeledproperdatasetineverytypeofdrivingcondition.Thisdatasetwillbeusedtotrain and evaluate our neuralnetwork.

II. LITERATURESURVEY

Table No. 1 : Literature Survey

Sr.no	Title	Authors	Methodology
1	An Empirical Evaluationof Deep Learning on Highway Driving.	Tao Wang, Sameep Tandon, Will Song, PranavRajpurkar, Brody Huval.	An Study Experiment of Deep Learning on Highway Driving have used deep learning and computer visions combined together to find a robust solution on autonomous driving which is relatively Inexpensive.

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2	Integrated recognition, localization and detection using Convolutionalnetworks.	Xiang Zhang,MichaelMathieu,Rob Fergus,YannLeCun	An included framework that helps using CNNs for place detection and classification.helpstousetheslidingwindowapproachefficientlywith CNN, and by combining both ideas it implements a featureextractor.
3	Deep neural networks for	Christian Szegedy,	We see a simple yet a powerful object detection system using DNNs
	Object detection. Advances in Neural Information Processing Systems	Alexander Toshev, Dumitru Erhan	which not only classifies but also does precise localization.
4	Towards fully autonomous driving: systems and algorithms. Intelligent Vehicles Symposium,	Jesse Levinson, Jan Becker, Jennifer Dolson.	By the use of the LIDAR system we generate high resolution maps of the environment which are used for localization with a close accuracy.

III. METHODOLOGY

A) VEHICLEDETECTION

Convolutional Neural Networks (CNNs)[2] are great image recognition systems from past years. A number of detectionnetworkswereadaptedfromthesesystemswhichledtothefurtheradvancementintheimagedetection. Here we look at a detection system which is capable of working at very low end laptops with GPU. As we are considering that we are using highway driving we need to ensure that the cars can be detected from minimum 100 mtrs length which requires a high resolution image. We are using the 640 X 480 resolutionimages.

By using the Overfeat CNN which will use the sliding window detector by using the results of each layer. The network which we have used has a stride size of 32 pixels. The neural network which we have used has a context view of 344 X344 pixels. To make sure that everything in the image frame is classified at least once we use skip gram kernals. By using the skip gram kernals we can take many different context views and using the different scales of the input image. We use mask detector to improve the issues of overfeat.[3]. The mask detector proposes the CNN to take the image input and object mask it through regression and highlight thedetails.

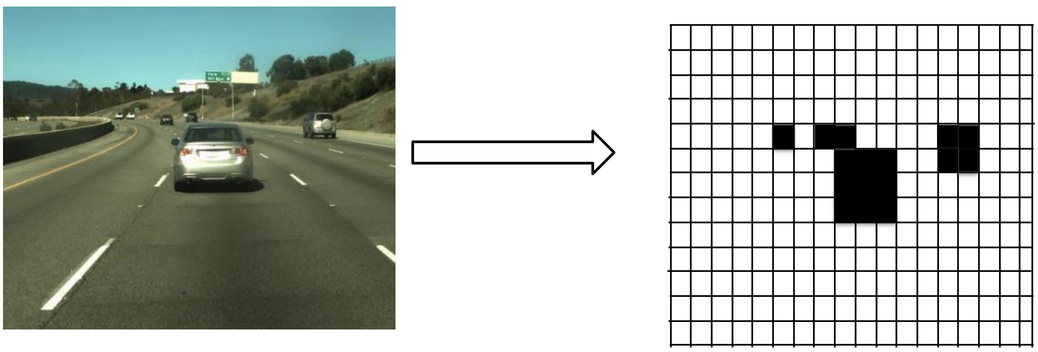


Figure 1: Mask detector

Bycombingthesetwoideastogetherandbytheuseofan Overfeat'sefficient"slidingwindow"detectorthathelps us create object masks and perform bounding box regressions. In the given figure we do not use skip gram kernel and use a full single image with resolution of 640 X480[3] .

We reduce the detector size on the top layer to 4 X 4 at the center of its context view. By the use of Opencv’s implementation of group rectangles we merge the bounding boxes based on similarity metric [3] Fig [2]

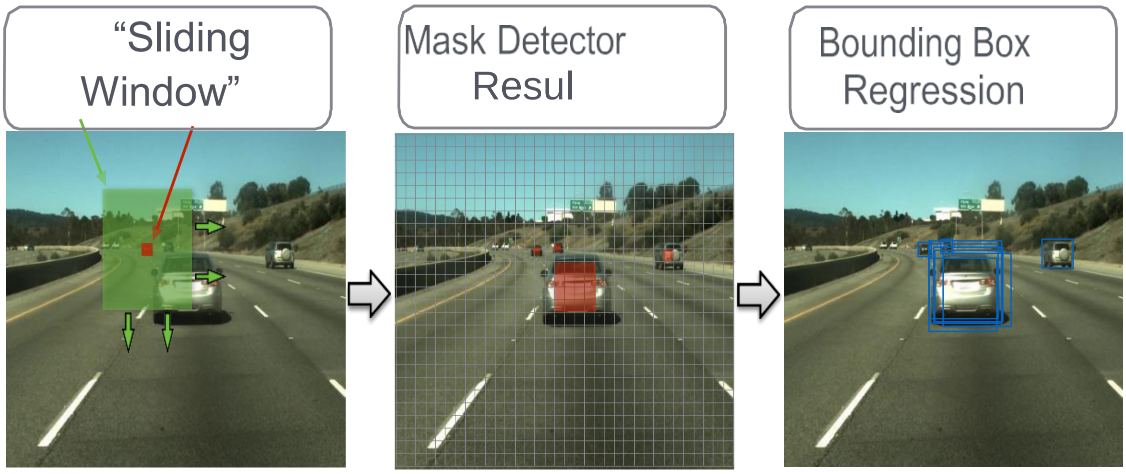


Figure 2: Overfeat Mask Detector

i) Highway Lane Detection

The CNN which were used for in vehicle detection, it can also easily be used to detect lane boundaries by adding some extra class functions to CNN. The track regression we used predicts a total of six dimensions. Where the first four dimensions represent the two ends of a line segment which is used for the lane boundary and the remaining two dimensions show us the depth or distance of the endpoints of the line segment with respect to positionsofthecamera.Thelinesegmentsonthenetworksarecolorcodedwithrespecttothedepthsastheclosest points of the line segments are red and the blue for the far ones. To obtain a semantic information about all the highway lanes we use [1]DBSCAN to collect the line segments together where each line segment represents the lanes. We use different colors are used to present different lanes. This clustering of the lanes together using DBSCAN can be seen in Fig 4.

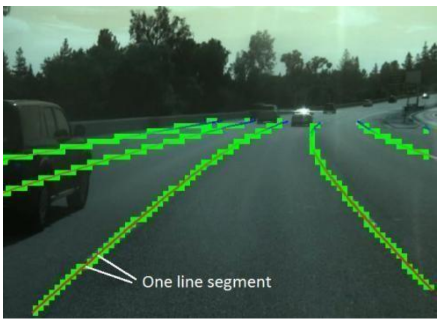


Fig 3: Laneboundary

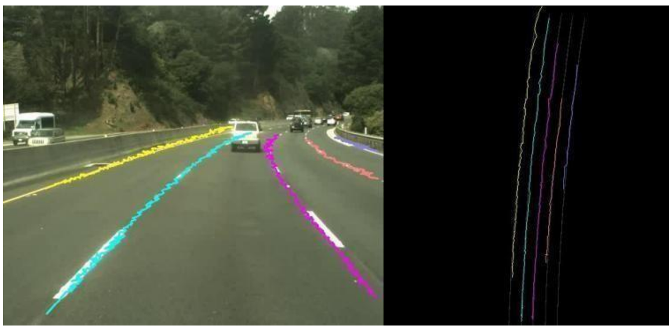


Fig 4: Lane detector after DBSCANClustering

B) EXPERIMENTALSETUP

1) Data collection

[1]The vehicle we have used for this experiment is a infiniti Q50 the car which was equipped with the following sensors:
6x Point Grey Flea3 cameras, 1x Velodyne LIDAR,
1x Novatel SPAN-SE receiver,
andthecarinfinitiQ50hasainbuildmediumrangeradarsystem.ThesesensorsalltogetherareconnectedtoaPC which has Core i7processor.
Once we create the videos for the dataset we annote the locations in 3D for vehicle the lanes as well for the acceleration of the vehicles.
ByusingtheVelodyneandGNSSsystemswecreatethemapsoftheenvironmentwhichmakeslabelingeasyand

straight forward. Then, we then filter the points based on LIDAR return intensity [4] and place it to preserve the lateral boundaries of the ego-lane. We then replicate the adjacent lanes of the lane boundaries to get a prediction for all adjacent laneboundaries.

Ego-laneboundarygeneration: Whilecollectingthedatawedonotchangethedrivinglanessothetrajectory path of our vehicle is clean and easy to estimate the shape of the road. By using few filter we can easily find the Ego lane boundaries. As we know that the highway lane boundaries are generally marked with backscattering materials,sowefirstfilter outlowreflectivesurfacessuch asasphalt.Thepointswhich reflectmaximumraysare considered. Then by filtering out the other surfaces such as cars and traffic signals with respect to the ground height,thenwefilterouttheunwantedgroundmarkingslikedirectionalsignsbyonlyconsideringmarkingswhose width is smaller than 2.2 m and higher than 1.4 m from thecar.

a) Generation of multiple laneboundaries:

During the information collecting series we determined that the lane distance is regular and adjustments best at few exceptions consisting of street merges or splits in highways. We can make a precise pre guess about the lane boundary by just shifting the Ego boundaries which are auto-generated laterally by multiples of the lane width. We have to rely on human to fix the lanes at the time of merges or splits.

Data Sets

[1]The data-set which has been used for the experiment consists of 14 days of car driving in San Francisco during summers in the months of April and June for a couple hours every day at the bay area .The data consisting nearly 17 thousand frames with vehicleannotationsand140thousandframeswithboundingboxesforthevehicles.Over 616 thousand frames contains the lane annotation samples. During the training for the system and translation, 7 different perspective distortions were registered to the raw datasets.

IV. RESULTS

The CNN that we used for the detection is capable to be used at 44Hz on a desktop-PC or a laptop which can be equipped with only a GTX 780 Ti.

TheFig[5]showsvisualratingswherebluedotsarerealpositiveresults.Thereddotsshowusfalsepositivesand the yellow dots show us falsenegatives.

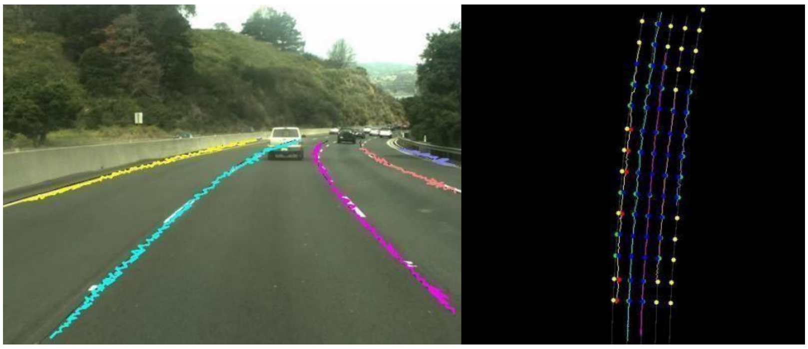
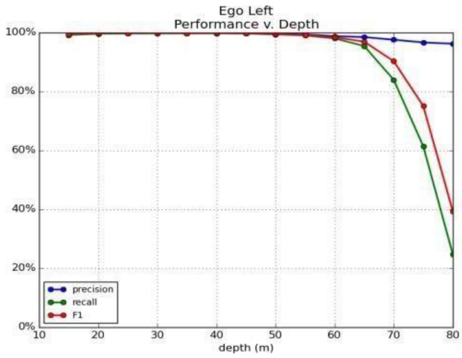


Figure 5: Lane prediction and lane detection

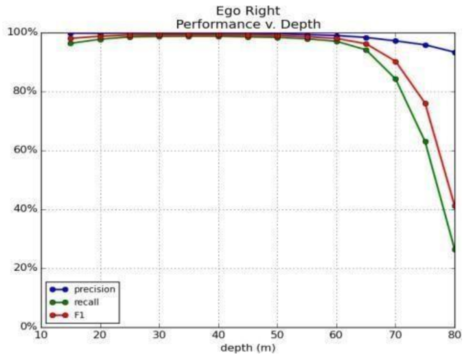
Fig 6 shows the combined accuracy results, and the score on all of the testing videos is shown by F1.

For the driving lane boundaries, we obtained a 100% of accuracy up to a distance of 50 meters.



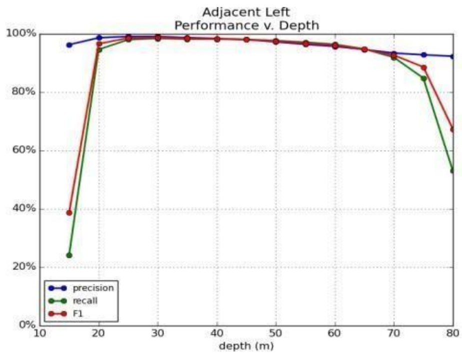
(A)

Figure 6(A): Ego-lane leftsideborder.



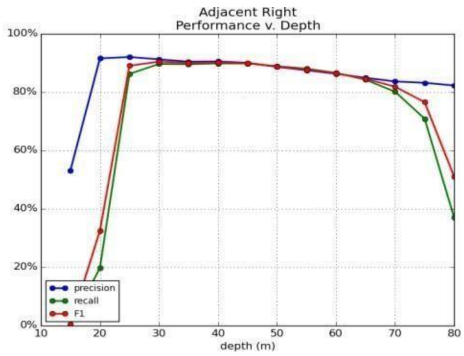
(B)

Figure 6(B): Ego-lane right sideborder.



(C)

Figure 6(C): Left adjacent lane leftsideborder.



(D)

Figure 6(D): Right adjacent lane right sideborder.

The bounding box predictions when matched with the ground truth. The work of our detection system as a depth function is in Fig 7

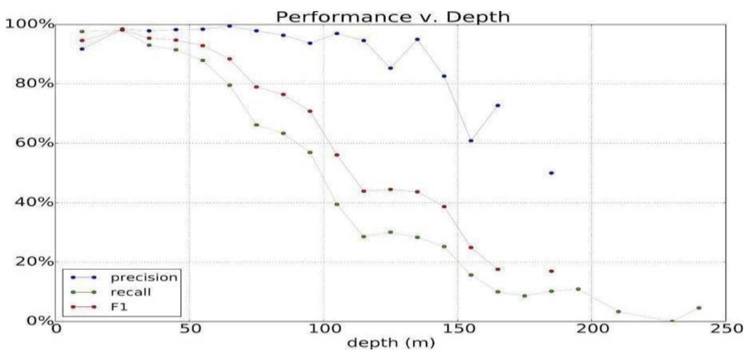


Figure 7: Car Detector Bounding Box Performance

We compared the results from our deep learning model to the Continental mid-range radar present in the car. This comparison is shown in Fig 8.

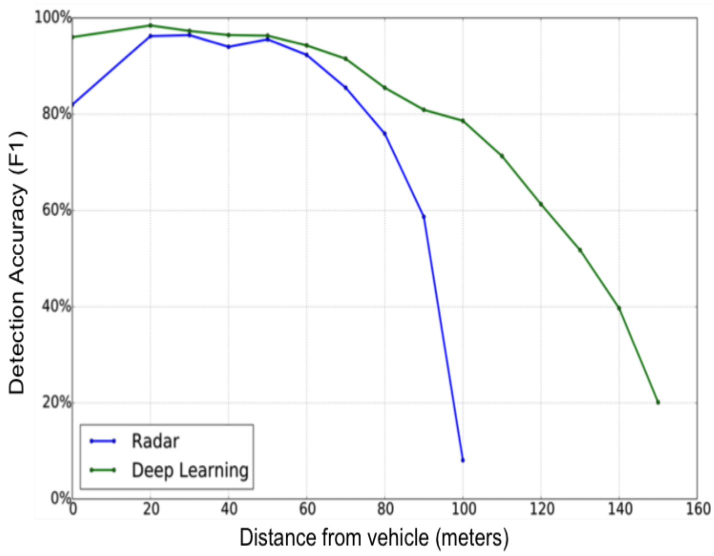


Figure 8: Radar Comparison

V. CONCLUSION

With the use of Cameras, Lidar, Radar, and GPS we created a set of videos of highway driving which consists of 17 thousand marks**,** which had bounding frames for vehicles, and a total of 616 thousand marks, which consist of images of motorway lanes**.** By using all this data we train the model by using the CNN architecture to detect the lanes and vehicles using only a single graphic gtx 780 Ti system which runs at 44Hz, which is good for real-time use. The results we get show that the CNN's we used are efficient of performing the detection on highway lanes andvehicles.Thefutureworkwillbetofocusontheworkingtogethighprecisiononagreaterrangewithabetter framework.

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