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Vehicle Collision Detection During Night Time

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***Abstract:** "Vehicle collision detection during night time" is an attempt to find an improved solution for vehicle detection problem, during night time. Night time vehicle detection is a challenging area since, the contrast between back ground and foreground is very less due to non uniform lighting, reflections, multiple light sources etc. This algorithm is a blend of night time image enhancement technique and fusion technique for fusing multiple features based on their weight. Image enhancement is an important aspect of the algorithm as it helps in improving the contrast between foreground and back ground as well as improving the lighting, so that it becomes easier to distinguish vehicle and other illuminated objects such as street lights. For improved reliability of the algorithm, set of complementary features - LBP (local binary pattern), HOG (Histogram of Oriented Gradients) and a CNN based feature - are used in the algorithm and are fused together using weighted fusion technique. For classification purpose, individual SVMs are trained for each feature and another SVM is trained for final rank based vehicle detection. Accurate region of interest in computed during detection phase, and is used for vehicle detection by trained SVM classifiers. Tail light detection is used for efficient region proposals. The algorithm is improved by leveraging the region proposals and high accuracy detection of Faster RCNN [10]. The algorithm detects multiple vehicles in single image frame and at possible multiple locations and distances within the frame.*

***Keywords :** ADAS, ADS, ROI, Night time vehicle detection, CNN, Faster RCNN.*

I. INTRODUCTION

Increasing population has demanded production and utilization of more number of public and private automobiles of various size and shape. It is also true that road and infrastructure is trying hard to catch up, leading to the necessity of more efficient sharing of available road infrastructure. Normal vehicle detection systems are not effective in night time scenario due to the fact that vehicle boundaries and features such as edges and corners are not legible during night time. So the most noticeable feature of a vehicle in night time scenario is its tail light. Here, we attempt to overcome the limitation of the night time images by relying on machine learning algorithms and training the algorithms with the right set of data and annotations. As part of this research, tried to implement an efficient algorithm for night time vehicle detection system, which can work as an early warning system for ADAS(Advanced Driver Assistance Systems) and ADS(Autonomous Driving Systems) use cases. The approach is divided into image enhancement, coarse ROI identification, feature extraction, training and detection phases . Three complementary features are used as the basis of classification and detection. The features are based on the 1)Convolutional Neural Network, Histogram of Oriented Gradient, and Local Binary Pattern. These features are used to train one classifier each, each of which is a support vector machine. A feature fusion technique is used for combining the features based on their weights. Score vectors from each feature classifier is used as the input for vehicle classifier, which finally fuses each feature based on their score. During detection, an accurate ROI(Region Of Interest) is found out by combining vehicle taillight detection with object proposals. Proposed method can deal with various scenes including vehicles of different types and sizes and those with occlusions and in blurred zones. It can also detect vehicles at various locations and multiple vehicles.

A. Importance of Vehicle collision detection during night time

Compared to day time, it is highly probable that driver may be fatigued and may lead to accidents. Drowsiness for a split second may be fatal. An error in decision for correctly judging the objects well ahead on time in low light and contrast can also cause accidents. In this scenario, ADAS (Advanced driver assistance systems play a major role in making things easy for the driver). They provide high levels of sophistication and can give clearer picture or warnings of the objects and acts as an early warning system which gives driver more time for judgment. This judgment time will definitely help driver is avoiding lot of accident situations and panic. Advent of ADS(Autonomous driving systems) enabled less intervention from human driver and most of the vehicle handling is done by the autonomous system, especially the situations like critical maneuvering the vehicle which needs high precision can be done easily with autonomous systems better than a human operator. The proposed algorithm can be used to help ADS also detect other vehicles during night time. ADS are already capable to take action based on the warnings.

B. Motivation

It is estimated that 30 percent of all vehicle accidents are caused by forward collision at rear end.

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The state of the art algorithm for night time vehicle detection has been tested to yield high accuracy of 95.95% detection rate and 0.0575 false positives per image. This is a fairly good result which implies that we may be able to avoid a large percent of accident probabilities and this gives confidence in driving, for night time vehicle handling. We know that even a small effective step towards early warning of accidents is critical for a life to be saved. Also deep learning and machine learning methodologies and image enhancement techniques are evolving day by day. The convolution network used for feature extraction in the state of the art algorithm is (FastRCNN). There was another algorithm with Overfeat acting as the CNN feature, which was studied. Overfeat was the winner of ILSVRC (ImageNet Large Scale Visual Recognition Competition) in 2013 and it was the first algorithm which was used for object detection task. It performed in detection, classification and localization tasks. There is scope for using improved networks for the feature extraction, which may yield better results. Also, better image enhancement methodologies should yield better results up to a certain degree. These all factors lead to take forward this research for improved results and sophistication. Possibility to enhance the scope of the detection so that it detects front headlights also would result in avoiding head on collisions.

C. Challenges

Based on the initial feasibility studies, it was found that there are limitations in current vehicle detection scenarios, which can be improved by the use of newer machine learning algorithms. One of the challenges was that some of the background also gets detected as vehicle tail light, due to less contrast between vehicle and back ground.

Another challenge was that there were bounding boxes constructed erroneously due to reflection on smooth surfaces.

Apart from the challenges identified, there is scope for improvements considering the fast improvements in deep learning algorithms and processing speed of computational devices.

Figure 1: Due to multiple light sources in the back ground, there are erroneous bounding boxes constructed.

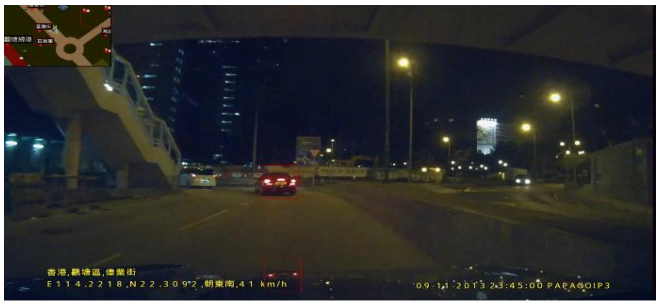

Figure 2: Due to reflection, there are bounding boxes constructed erroneously.

D. Approach of research

Extensive literature survey is conducted, which provide sufficient insights on various aspects of night time vehicle detection requirement. Papers on basic image processing required for threshold specific to night time images, ROI extraction, image enhancement during night time etc. are covered in the literature survey. Conducted feasibility study to analyze the reconstruction of the existing state of the art algorithm considered for analysis. Reviewed supervised learning methods for classification suited for the night time scenario.

E. Objective

Based on the literature survey and feasibility study, identified the scope for improvement in the accuracy of the algorithm and objective is to implement a reliable and accurate night time vehicle detection system with state of the art accuracy, which should be effective in identifying multiple classes of vehicles and multiple vehicles and may extend to possible non vehicle targets which are known. The motivations mentioned have inspired to opt such a topic for further research. It was followed by extensive literature survey and the methodology formulation based on how researches in similar areas are being conducted. Tools were identified based on easiness of implementation and usefulness.

II. LITERATURE SURVEY

A. Survey of related papers

Chang et al. [6] developed LIBSVM library for Support Vector Machines (SVMs). They had been actively developing this package since the year 2000. They aimed to help their users to apply SVM to their applications without any difficulties. LIBSVM could gain ample reputation among machine learning enthusiasts and machine learning application developers and many other related areas. They are known for their effectiveness in solving issues like solving SVM optimization problems, multi-class classification, theoretical convergence, probability estimates, and parameter selection etc. Dalal et al. [1] considered linear SVM based human detection as a test case and conducted studies on the question of feature sets for robust visual object recognition. They reviewed existing edge and gradient based descriptors. Based on these studies, they could arrive at the conclusion experimentally that grids of Histograms of Oriented Gradient (HOG) descriptors significantly outperformed existing feature sets for human detection. Based on the analysis of the various scenarios in machine learning application, there are a few computation stages that are involved in the machine learning algorithms. The influence of each of those computation stages on performance was also studied. It was understood that that the stages such as fine-scale gradients, fine orientation binning, relatively coarse spatial binning, and high-quality local contrast normalization in overlapping descriptor blocks etc. are important for achieving good results with any such machine learning algorithms. The approached based on the above observations gives nearperfect separation on the original MIT pedestrian database. Effectiveness of the modified algorithms were tested on a more challenging dataset containing over 1800 annotated human images with a large range of pose variations and backgrounds.

Felzenszwalb et al. [?] described an object detection system based on mixtures of multi-scale deformable part models(DPMs). The proposed system was able to represent highly variable object classes and achieves state-of-the-art results in the PASCAL object detection challenges. Until 2010, the effectiveness of deformable part models had not been established on difficult benchmarks, such as PASCAL data set, even though they had been quite popular at the time. The system relied on new methods for discriminative training with partially labeled data. Felzenszwalb et al. combined a margin sensitive approach for data-mining hard negative examples with a formalism which was known as latent SVM. A latent SVM is a reformulation of MI-SVM in terms of latent variables. A latent SVM is semi-convex, and a training problem which uses latent SVMS will become convex once latent information is specified for the positive examples. This would result in an iterative training algorithm that alternates between fixing latent values for positive examples and optimizing the latent SVM objective function. Proposed system relied on 1) new methods for discriminative training of classifiers which make use of latent information and on 2) efficient methods for matching deformable models to images. The resulting system is both efficient and accurate, leading to state-of-the-art results on difficult data sets. Tehrani et al. [?] proposed a method based on using latent parts to optimize the structure in Deformable part models (DPM). By the time, DPMs had been already proved to be of great performance, especially for objects detection. Many extensions of DPM had been already published in literature too. DPMs generally have high performance, though they dramatically fail to detect objects in a few challenging environments such as during night time. The paper proposed a method based on the idea of latent parts to optimize the structure of objects in deformable part models. Even in challenging environment some parts of objects would be still visible and using latent parts optimization, the structure of DPM's object model was able to catch significant features. The proposed method by Tehrani et al. underwent thorough evaluation under night time car detection scenario. These experiments were done in urban area and IR camera was used. Night time vehicle detection is a challenging problem due to low visibility, light distortion and non uniform illumination, glare and reflections in urban scenario. Regardless of all these conditions it was proved experimentally that the method was very effective to detect close and medium range cars in urban scenes at night time. Girshick et al. [?] postulated that Deep pyramid Deformable Part Models can be represented with corresponding layers of CNN [?]. DPMs and CNNs are two of the widely popular methods are two widely used tools for visual recognition or classification. Until this time, they were considered as two distinct approaches. DPMs are in fact graphical models implemented based on Markov random fields, while CNNs could be considered as "black-box" and was a good example of non-linear classifiers. In the paper, Girshick et al. proved that it is accurately possible to map DPM functional layers to corresponding CNN layers, thus providing a new insight into the theoretical and practical application and understanding of the two approaches. Their DPM inference algorithm could unroll and map each step of DPM to an equivalent (and at times, more suitable) CNN layer. With this new insight, it was not at all a difficult task to replace the standard image features used in DPM with a learned feature extractor(based on CNN) trained for the purpose. Resulting model was named as DeepPyramid DPM and was experimentally validated on PASCAL VOC data set. DeepPyramid DPM significantly outperformed DPMs based on histograms of oriented gradients features (HOG) and slightly outperformed a comparable version of R-CNN detection system, while running an order of magnitude faster. As it was already established that CNNs were the most effective approach for classification and detection tasks involving complex scenarios, Zhang et al. [1] put forward an integrated framework which used Convolutional Networks for classification, localization and detection. They could prove a multi-scale and sliding window approach could be efficiently implemented within a Convolutional Neural Network. They postulated a novel deep learning approach for localization by learning to predict object boundaries. They increased the Bounding boxes by accumulating them as detection confidence was increased, rather than suppressed. They showed that different tasks could share a single network and was able to train them simultaneously using the single shared network. The resulting integrated framework won the localization task of the ImageNet Large Scale Visual Recognition Challenge of 2013 (ILSVRC2013) and obtained very competitive results for the detection and classifications tasks. Post-competition, they successfully worked for establishing a new state of the art for the detection task. They released a feature extractor from their best model called OverFeat. Based on analysis of convolutional neural network(CNN) based features, Razavian et al. [7] inferred that the generic descriptors extracted by the CNN were very powerful. They could collect ample evidence to prove this. They reviewed and conducted several experiments consisting of different recognition tasks using the publicly available code and model of the OverFeat network. The OverFeat network had been trained to perform object classification on popular Large Scale Visual Recognition Challenge 2013(ILSVRC13). They could successfully use and validate that features extracted from the OverFeat network could be used as a generic image representation to perform a diverse range of recognition tasks, object image classification, scene recognition, fine grained recognition, attribute detection and image retrieval tasks on a diverse set of datasets. OverFeat network was trained to solve some classification and detection, but they selected multiple other tasks and datasets than OverFeat was designed to solve. Astonishingly, they could obtain consistent superior results compared to the highly tuned state-of-the-art systems in all the visual classification tasks on various datasets. These observations pointed at the generic nature and applicability of the features extracted to different tasks. For instance, retrieval task consistently outperformed other low memory footprint methods except for some customized datasets. The results were achieved using another linear SVM classifier (or L2 distance in case of retrieval) applied to a feature representation of size 4096 extracted from a layer in the net. The representations were further modified using simple augmentation techniques e.g. jittering. The results strongly suggested that features obtained from deep learning with convolution nets should be the primary candidate for feature vector for future visual detection tasks. Kuang et al. [1]

further improved the CNN features by image enhancement technique such as multi-scale retinex (for image enhancement)(MSR), region of interest(ROI) extraction and object proposals based on vehicle light detection. An improved version of multi-scale retinex (MSR) improved the accuracy of ROIs and enhanced images for accurate nighttime vehicle detection. They combined the CNN feature with four other complementary features by fusing with the help of a score-level feature fusion method. For conducting this study, a customized nighttime vehicle dataset was developed. Experimental results revealed that the proposed nighttime image enhancement method, score-level multi-feature fusion and ROI extraction method were all effective for nighttime vehicle detection. The state of the art night time vehicle detection method demonstrated 93.34% detection rate and outperformed Deformable Parts Model (DPM) and Convolutional Neural Networks features with SVM (CNN+SVM) by 6.6% and 42.4% at 0.165 False Positives per image (FPPI). The state of the art method could detect blurred and partly occluded vehicles, as well as vehicles in a variety of sizes, numbers, locations and backgrounds.

B. Summary

Based on the literature survey, found out that there is scope for improvement in the accuracy of the night time vehicle detection algorithm, with the use of latest machine learning algorithms and approaches suitable for object detection.

III. THEORETICAL BACKGROUND

The typical use case scenario of night time vehicle detection is for the video footage captured by the on board dash cam module be further processed with the proposed algorithm. Real time performance is a mandatory requirement for the use case. The training of the system is the one which consumes lot of time. Once the training is successfully done, system can be deployed and can be used for detection. For the development of the system, a night time data set can be utilized and be trained using PC with high end configurations and weights be transferred to the on board computers capable of image processing. This report describes image processing approaches based on night time data set. General object detection consists of three main stages. i) Region proposal ii) Classification iii) Post processing. Region proposal is the stage in which object region is identified in which object could be located in the image. Once the co ordinates of this region are identified, need to check whether this region encompasses the possible objects of interest. The presence or absence of certain object in a certain area is decided by looking for corresponding feature vector (constructed from the object using some approach such as CNN feature extraction) in the encompassed area. Once a match is found, post processing algorithms can construct the bounding box, then labeling of the bounding box with the class of object identified and can predict the probability for the object to belong to the specified class. It is possible for the algorithm to have internally more than one class label for the same bounding box, but algorithms decides which is the actual label to be displayed, based on maximum probability score or non maximum suppression.

A. Night time image enhancement

The issue with the processing of night time images is that the contrast and brightness may be low most of the time and edges and color may be less pronounced. So, features which rely on color and edges may be a bit unclear to a certain extend. This prevents it from meaningful feature extraction. Night time image enhancement aims at improving the contrast and brightness of the night time image. Another objective is to reduce noise. A biologically inspired image enhancement technique is used for enhancing the image. This algorithm is named Multi Scale Retinex(MSR). This image enhancement technique is inspired from the biological visual system. Retinal information processing mechanism begins with the sampling by rod and cone photoreceptors. The red (R), green (G), and blue (B) components of the input image are processed respectively by 'long', 'medium', and 'short' -wavelength cone photo receptors of the retina. Similarly, in the proposed algorithm, the input image I(x,y) is converted to channel images Ic(x,y) corresponding to R,G and B channels. Then brightness of the image is extracted from these individual signals using an averaging technique.

$$HC_{in}(x,y) = 1/3\sum_{n=1}^{3} lc(x,y) \tag{1}$$

Where HCin is the input horizontal cells, which is the brightness of the input color image, which is a normalized value. The horizontal cells collects the input from each photo receptors R,G and B and performing another averaging operation. This operation can be viewed as a convolution operation of input of horizontal cells and a scale function

$$g(x,y,\sigma l(x,y)) \tag{2}$$

which is modulated by light and local contrast. In fact standard deviation is modulated by light and local contrast.

The scale function of HCs is determined by the gap junctional coupling that is modulated by the light. Under dim starlight condition (low brightness), the conductance of the gap junctions is relatively low (small RF). As the ambient background light increases to twilight condition (intermediate brightness), the conductance increases (large RF). Under bright daylight condition (high brightness), the conductance is reduced again (small RF). In short, the output of horizontal cells is a modified version based on light and local contrast.

B. ROI Extraction

The ROI (Region Of Interest) is extracted based on the position of vehicle rear lights. First, the possible vehicle tail light regions are detected using the following steps: i) converting the RGB images to intensity images and reducing noise using an empirical threshold (0.4). ii) position reliability checks which can be used to detect vehicle rear lights. The additional check can be height alignment or height difference between a pair possible rear light area, whether they are part of a connected body (made sure with region growing segmentation approach) etc. iii) Coarse ROIs are calculated with each ROI associated with a score measuring its likeliness to be an object are extracted by applying EdgeBoxes on the enhanced images. iv) Finally, a new score function that combines the coarse ROIs' scores and vehicle taillight detection together is constructed to calibrate scores and obtain more accurate ROIs. Possible rear light region(ROI) is passed over to image enhancement method for further processing .

C. Feature Extraction

The ROI extracted from the image after going to the image enhancement is used for feature extraction. There are 3 features used for the algorithm. LBP (Local binary pattern), HOG (Histogram of oriented gradients) and CNN based feature (extracted using FastRCNN).

D. Local Binary Pattern

Local binary pattern computes the difference in intensities between a centre pixel and surrounding pixels and encodes the difference into an 8 bit value. Algorithm, then creates the histogram of all possible values of such 8 bit combinations for an image. This histogram can have values ranging from 0 to 255. This gives a two dimensional array, which is the feature vector.

E. Histogram Of Oriented Gradients

Vertical and horizontal gradients are calculated for the image using Sobel operations and the values are used for finding magnitude and direction. Then histogram is constructed with the magnitude values corresponding to different angle bins. We use unsigned bins(varying from 0 to 180 degree) and 0 to -180 are also represented using the values in the range 0 to 180. This gives a two dimensional array, which is the feature vector.

F. CNN based feature

Using DPM (Deformable Part Model), it is possible to extract feature vector which is variant of HOG. DPM can be represented to represent an image as a group of parts and connecting spring between each part so that individual parts can move about the spring, which can capture image deformations. CNN networks such as OverFeat successfully implemented DPM feature extraction using convolution network. Such a feature can be used as a CNN based feature for night time vehicle detection purpose along with LBP and HOG features. Fast RCNN [?] based feature extraction was used for the implementation, as it gave better performance compared to Overfeat based CNN feature.

G. Feature Classification

Set of 3 complementary features extracted can be used to train a libSVM classifier each, which should be able to produce a score for the feature for the vehicle. Fivefold cross validation is carried out using each individual feature. The score indicates how closely it is able to detect a vehicle or what the confidence is for the object to be a vehicle. These trained SVMs should be able to produce the ranks during detection phase.

H. Vehicle Classification

Individual ranks produced by the individual features are used to train a libLinear based classifier, which classifies each class of vehicle, on the basis of score for each feature. This feature fusion scheme ensures that the features are fused in a complementary fashion. This is ensured by the vehicle classifier as during training of the vehicle classifier, the ranks of each features are fused based on training data. This mechanism makes sure that the feature scores are added based on how much each rank contributes to final vehicle detection in the training data.

I. Vehicle Collision Detection

Using camera parameters such as focal length, vehicle class detected and distance from camera, in the image a classifier will be trained to predict collision probability. Training time, it is assumed that camera parameters remain fixed. Based on the training, collision probability can be predicted at detection time. While training the images took care to ensure that the vehicles which applied breaks and those with brighter red light in the tail is given more preference to be detected as the vehicle.

IV. EXPERIMENTS AND EVALUATION

Implemented a framework which is able to take video input as well as image input and execute the algorithm for night time vehicle detection. The pre-processing, segmentation and region proposal stages gave expected results, as they could accurately identify and detect vehicles.

A. Experimental setup

The experimental set up consisted of cloud based virtual machine provided by Google colaboratory, with NVIDIA Tesla K80 GPU used for training the CNN, and SVMs. Google Colaboratory is a free Jupyter notebook environment that requires no setup and runs entirely in the cloud. However, need to install additional packages like specific version of Keras etc. With Colaboratory, we can write and execute code, save and share our analyses, and access powerful computing resources, all for free from our browser. For testing and other intermediate processing, visualize and manipulate data set etc. another intel P5 based Ubuntu 16.04 based PC was also utilized. Used Keras with Tensorflow backend for training the CNN. The trained weights and config.pickle file are copied to Ubuntu16.4 PC for carrying out data set from night time image data set, Ubuntu 16.4 with python. The program was designed to take both image and video inputs in separate modes of operation.

V. TRAINING AND DETECTION PIPELINES

The architecture in Figure 3 shows both test and train pipelines. Upper portion is training pipe line where training images are fed to the pipeline and training is performed, result of which is the weights learned from SVMs and Vehicle classifier. These training cycles are independent in that individual feature SVMs need be trained separately and using the output scores of these SVMs, we need to train the vehicle classifier. Moreover, the CNN for feature extraction need be trained separately. The modified architecture as in Figure 4 solves the problem of multiple training with the use of Faster RCNN as the CNN engine. In this case, due to the fact that Faster RCNN has region proposal sub system, many architecture blocks can be optimized out and a modified architecture as in 4 will result. This insight is evident from the fact that earlier approach of combining hand crafted features and SVM can be comfortably replaced with newer approach of automatic feature map creation within CNN networks.

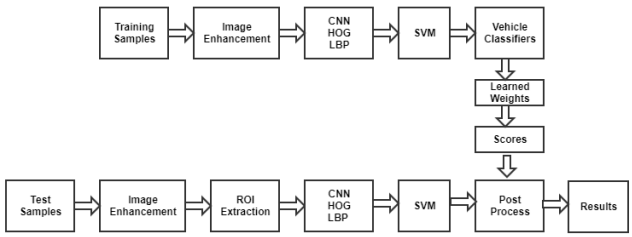

Figure 3: Training and testing pipelines for tail light based ROI identification based algorithm

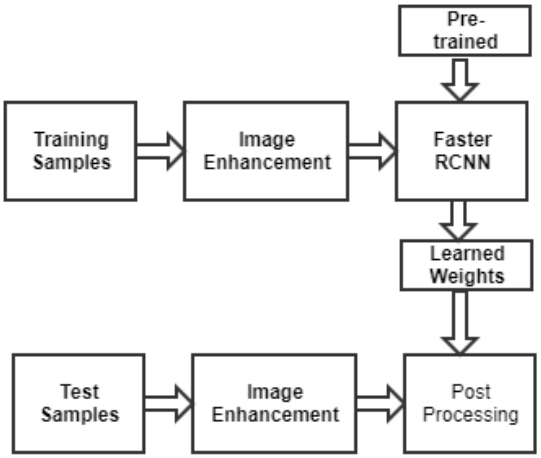

Figure 4: Training and testing pipelines for the Faster RCNN based algorithm

Even though the presence of complementary feature fusion is not there in the new architecture, the new architecture will give good results for the use case.

A. Data Set

Night time image data set was downloaded from [12]. The images had both test and training data set. Test data set consisted of smaller size images(which was only car rear images without background, corresponding to different vehicles), while training images were larger images including car and background (Similar to images captured by an on board camera). Using a labeling tool [?], the PASCAL VOC compliant annotations of the bounding boxes were created in order to train the Faster RCNN network with bounding box details.

B. Labelling tool

Used an image labelling tool [13], to label the images as the bounding boxes around the vehicles and objects were not available from the downloaded data set. This tool creates annotations in the form of XML files, compatible to PASCAL VOC data set [14].

C. Evaluation Criteria

Evaluation criteria are that the object detection should happen at various night images with good Mean Average Precision. The following parameters can be used to measure the accuracy of object detection.

1) Precision & Recall: Precision is the measures which shows how accurate is the prediction i.e. the percentage of the algorithm's predictions are correct. Recall is the measure of how good our algorithm can find all the positive inputs, i.e. we can find some 90% of the possible positive cases out of our top N predictions. Here are mathematical definitions: For example, in the testing for vehicle detection:

2) IoU (Intersection over union): IoU is the measure of the overlap between 2 boundaries. We use that to measure how much our predicted boundary overlaps with the ground truth (the real object boundary). In some data sets, we predefine an IoU threshold (say 0.5) in classifying whether the prediction is a true positive or a false positive.

D. Detection results with tail light based algorithm

The figures in Fig: 5 shows the results obtained when tail light based algorithm was used. Fairly good results were obtained.

Figure 5(a-e): Object detection with night time vehicle detection

The accuracy was much better when Faster RCNN based algorithm was used

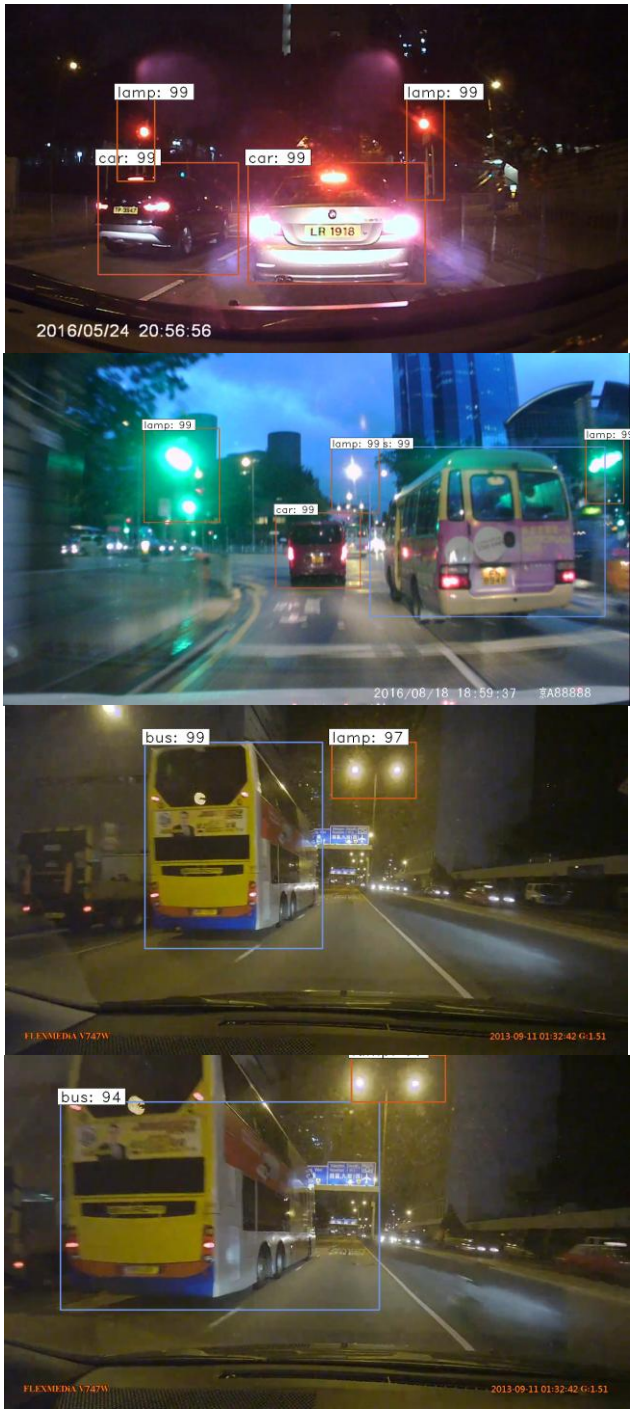

Figure 6(a-d): Night time vehicle detection algorithm is able to detect

VI. RESULTS

Was able to detect vehicles during night time scenarios well in advance, which can act as early warning to the driver. Multiple vehicles in the scenario w vehicles tested and corresponding areas were marked with circles.The implementation using red light identification was improved with Faster RCNN. The Faster RCNN based implementation was able to detect back ground objects as well when trained to do so. It detected lamp posts also along with vehicles as shown in 5 Both these set ups had their advantages and disadvantages. 1) Use of segmentation based region proposal had the advantage that there had been smaller number of region proposals if the image consisted of less number of vehicles or light sources, where as in the case of cluttered traffic scenario, due to many red light sources and occlusion, it had less accuracy. 2) Use of Faster RCNN had more number of region proposals, but it is accurate even in cluttered environments and occluded objects. When the training images provided with the data set was used for training, it was observed that the bounding boxes were not accurate and bounding boxes were enlarged. This was rectified when the data at the same scale as the test images were used for training. This indicates the requirement for a scale invariant algorithm.

VII. CONCLUSION

1. The algorithm for night time vehicle collision detection performs faster than the existing state of the art algorithms for night time vehicle detection in that it is giving highaccuracy results.
2. In many frames, it is able to detect the vehicle with 99% accuracy.
3. It is able to detect car, bus, and even lamps correctly.
4. The requirement of multiple training passes in the training pipeline is avoided by using Faster RCNN and its internal region proposal mechanisms.
5. However, there can be further improvement if we use latest deep learning algorithms and GPUs and Parallel GPUs for testing and training. Many vehicles platforms started coming with on board GPU support which is promising for implementing the algorithm with reduced test time.
6. Scale in-variance is another nice to have feature for night time vehicle detection scenario, where we can train the network with image and available scale and during detection time, system is able to detect the vehicle, even though it is at a different scale.

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