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Forward Collision Warning System Based on Tensor Flow

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ABSTRACT: This project deals with constructing a prototype of driver assistance system using image processing techniques in order to solve the issues of road traffic and accidental deaths thus ensuring safety of civilians in the road network with smoother vehicular pavements. Vehicle detection and pedestrian detection are proposed in the project which is then implemented and adopted in intelligent vehicles. The Vehicle detection and tracking process is done using image processing and deep learning methodology. It helps in detecting the stationary as well as the movable objects on the road. In the system, the images analysis is done using advance image processing techniques for obstacle detection which is further accompanied by evaluation of sequences of images recorded that give information about the automotive environment which has to be analyzed to help the driver. Therefore, the system allows the driver to carry on his/her journey smoothly and alerts regarding obstacles at frequent time intervals. In this paper, we present you the preliminary results using only camera images for detecting various objects using deep learning network, as a first step toward multi-sensor fusion algorithm development. Encouraging results are obtained by the simulation experiments based on camera images where the proposed deep learning network based detection algorithm was able to detect various objects with certain degree of confidence.

KEYWORDS: Image Processing, Deep Learning, Car Dashcam, Python, OpenCV, SoloNet Tensorflow Model, CNN (Convolutional Neural Network).

I. INTRODUCTION

Forward collision warning system (FCWS) and autonomous driving are promoted by major OEMs and researchers as the technology of the future automobiles. Many aspects of the active safety systems in automobiles that currently exist (e.g. collision avoidance system, lane keeping assist, blind spot detection, adaptive cruise control) can provide the basics of an autonomous vehicles' framework. However, many challenges remain with the current state of the art in DAS technologies that hinders safe and robust implementation of the autonomous vehicles for consumers. One of the key challenges is real-time detection and identification of a moving object of various shapes and speeds under all possible environments and backgrounds. For object detection and classification, image and video data from camera is the only information source in the existing methodologies [1-7]. However, merely image data is not able to deliver real-time and high performance—what is needed for autonomous vehicle. So some recent works are focusing on sensor fusion. For example, Chavez-Garcia et al. [8] used LIDAR, RADAR, and camera in fusion for moving object detection in the vehicle setting. However, their image detection methodologies use HOG (histogram of oriented gradients)

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descriptors as feature, whose performance is much poorer than the performance of recently proposed deep learning approaches.

II. LITERATURE REVIEW

DEEP LEARNING BASED METHODS FOR OBJECT DETECTION

For DAS and autonomous vehicle, achieving high detection performance and near-real-time object detection on an embedded system is a key requirement. Among different classification algorithms, cascade classifier is one of the fewest algorithms that can meet this requirement. The key to its high performance is the use of integral image, which only performs basic operations in a very low processing time. However, a crucial limitation of cascade classifier is that it works only for fixed aspect ratio. Viola and Jones [9] have overcome this limitation by designing rectangular Haar-like features and then use these features with AdaBoost learning algorithm combined with a cascade of strong classifiers. Then Leinhardt and Maydt [10] have improved the set of Haar-like features. In another work, Ahonen et al. [11] applied Local Binary Patterns (LBP) for face detection and obtained good results compared to Haar-like results. Since then, both Haar-like and LBP has been used extensively for object tracking in real time. They are also implemented in OpenCV (opencv.org), an optimized C++ library for computer vision applications. Meanwhile, machine learning community had been working on learning features from raw images using multiple layers of non-linearity, leading to deep learning. Early example on these are Restricted Boltzmann Machines [12], Deep Belief Networks [13], and Stacked Autoencoders [14]. The main idea of these methods is to learn features in an unsupervised manner so that a pre-train model can be built, which works as a good initialization for subsequent supervised classification system. Later in 2012, Krizhevsky et al. [13] proposed a Convolutional Neural Network (CNN) based deep learning model, which brought down the error rate on a benchmark classification task (ILSVRC competition) by half, beating traditional hand-engineered approaches. Importantly, CNN can achieve this performance by an end-to-end supervised training, without the need for unsupervised pre-training. Since then, CNN and its various architectures has become the best tool for real-time object classification from image data [1-5, 15-16]. A recent survey on CNN [17] discusses different CNN architectures along with their successful applications for object recognition in different domains. In this ongoing work, we are using CNN along with sensor fusion for better object recognition in real-time for supporting DAS and autonomous vehicles.

III. TENSORFLOW DETECTION API

The Tensorflow Detection API brings together a lot of the aforementioned ideas together in a single package, allowing you to quickly iterate over different configurations using the Tensorflow backend. With the API, you are defining the object detection model using configuration files, and the Tensorflow Detection API is responsible for structuring all the necessary elements together.

PROTOS

In order to have a better understanding of what the different supported components are, have a look at the 'protos folder' which contains the function definitions. Especially, the train, eval, ssd, faster_rcnn and pre-processing protos are important when fine-tuning a model.

SSD (Single Shot Multibox Detector)

The SSD architecture was published in 2016 by researchers from Google. It presents an object detection model using a single deep neural network combining regional proposals and feature extraction. A set of default boxes over different aspect ratios and scales is used and applied to the feature maps. As these feature maps are computed by passing an image through an image classification network, the feature extraction for the bounding boxes can be extracted in a single step. Scores are generated for each object category in every of the default bounding boxes. In order to better fit the ground truth boxes adjustment offsets are calculated for each box. Different feature maps in the convolutional

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network correspond with different receptive fields and are used to naturally handle objects at different scales. As all the computation is encapsulated in a single network and fairly high computational speeds are achieved (e.g. for 300×300 input 59 FPS).

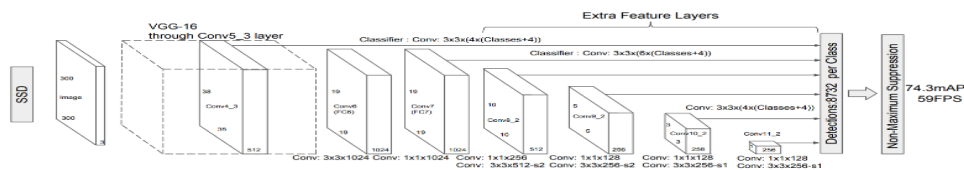


Fig: 1 The SSD network leveraging feature maps from VGG-16

Faster R-CNN

Faster R-CNN was developed by researchers at Microsoft. It is based on R-CNN which used a multi-phased approach to object detection. R-CNN used Selective search to determine region proposals, pushed these through a classification network and then used an SVM to classify the different regions.

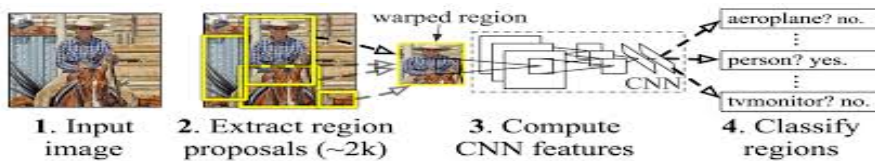


Fig: 2 An overview of the R-CNN architecture. The NMS phase is not shown.

Faster R-CNN, similar to SSD, is an end-to-end approach. Instead of using default bounding boxes, Faster R-CNN has a Region Proposal Network (RPN) to generate a fixed set of regions. The RPN uses the convolutional features from the image classification network, enabling nearly cost-free region proposals. The RPN is implemented as a fully convolutional network that predicts object bounds and objectness scores at each position.

IV. DISTANCE MEASUREMENT FOR FORWARD COLLISION WARNING SYSTEM

We further implement our simplified R-CNN model for forward collision warning system in DAS. That is, after we detect the vehicles and pedestrian, we need to estimate the relative distance of the detected objects. To determine the distance to a detected object, we must first locate the line of contact between the object and the road and then compute from the geometry of pinhole model shown in Fig.

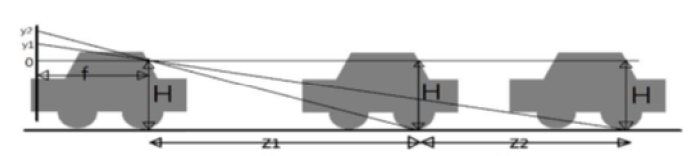


Fig: 3 Pinhole model for detected objects (using vehicle as example)

V. METHODOLOGY

It is observed that the accuracy in detecting and localizing a moving object still lacks robustness when environmental and surroundings change. In this work, as a first step toward sensor fusion based deep learning, we utilize the deep learning technique using only imaging data to detect a moving object under varying environment and surroundings.

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The deep learning algorithm allows us to learn the environmental conditions and background with higher degree of accuracy which in turn helps improve the accuracy of detection, localization, and classification of the object in the foreground. Camera images are converted into pixel level data which are processed to remove foreground. This image data are segmented and then all segmented data are structured in the form of a tensor. The tensor data is then fused with the distance detection data. This composite tensor is then further processed to optimize bounding box. At this point, the data is ready to be using the deep learning algorithm via CNN. The methodology deals with object tracking and classification in order to detect different obstacles traversing at different speeds and designing ways to implement learning the process of detection.

The following steps are proposed to be included in the overall algorithm.

1. Classification of unlabeled data obtained from the camera.
2. Calculation of distance from the object indicated and estimating the error found from the Video data.
3. Determination of the size of the object from the video by a prior knowledge of the specified class.

This paper focuses on the real-time detection of objects in continuous images (or video) captured with the dashboard camera of a moving vehicle. For object detection, deep learning based machine learning methodologies is used. A trained detection model was used. The detection can be performed in real-time on real-life camera data mounted on vehicle dashboard. For detection task, a learning model which can detect the following three objects: pedestrians, bikes and cars is developed.

VI. EXPERIMENTAL RESULT

To verify the effectiveness of our method, we implement it in Python using OpenCV library on 64-bit windows. The hardware platform is a laptop, running with an Intel® Core™ i5 1.60GHz 1.80GHz CPU and 8.00GB RAM. The videos prepared for testing is recorded through an automobile dashcam recorder whose frame rate is 24 fps, and their resolution is adjusted to 1920*1080p. Next, to evaluate the accuracy of the vehicle tracking and distance measurement, a car right in front of our car is prepared as the tracking target, and the distance is measured by our method. The test is carried out in various situations: driving speed can be low or high, while the distance can be near or far.



Fig: 4 Result during Day

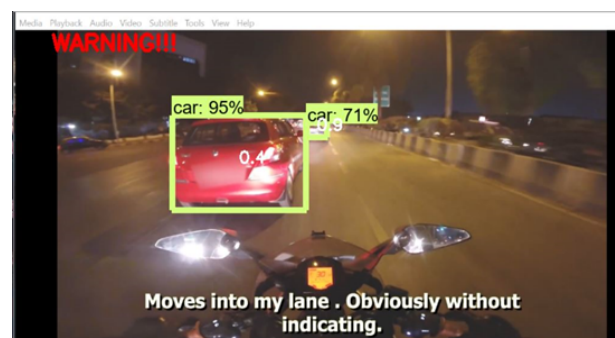


Fig: 5 Result during Night

VII. CONCLUSION

Although the bottleneck faced by researches using cameras in ADAS systems is the strong demand of computing power for video processing, the IC industry are making great progress in the development of fast video processors which makes complex algorithms about vehicle detection and vehicle tracking possible [18]. Our paper presents a forward collision warning system that can detect other vehicles appear in front of the car on road and track them, measure their distance to warn the driver when the distance is too close which can potentially cause an accident. Experiment result have shown that our detection method has a high detection rate, and our tracking and distance measuring method has a high accuracy in real environment. Further analysis of road environment is still needed, in order to make the results more precise. Moreover, some of the algorithms we used are still too computationally

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expensive to be deployed on embedded platforms, so minimized and fast-speed version of these algorithms are expected to be studied. Last but not least, exploration of high level semantic information such as vehicle behaviour could be beneficial, and will pave the way for more sophisticated functions concerned with the possible future of road traffic, namely automated driving.

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