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Comparison of Vehicle Detection Techniques applied to IP Camera Video Feeds for use in Intelligent Transport Systems.

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Abstract

Vehicle detection is an important area in Transport and Artificial Intelligence. Through vehicle detection techniques, vehicles can be located across different images. Some of these models are robust enough to identify parts of a vehicles in images where the vehicle might be partially occluded. Recent advances in detection methods gave rise to a range of different techniques that can be used for recognition and detection of vehicles. Although each technique has its merits, it is not always the case that the adopted model works well for scenarios involving IP Cameras. The motivation for this study is to compare a number of state of the art techniques including deep learning models and computer vision approaches. A set of experiments are developed in order to test these models on a number of low quality IP camera footages set in the transport domain in order to measure detection and recognition accuracy. The final evaluation compares detection accuracy using mean average precision, the semantics of the recognised vehicle as well as recognition robustness when applied to a dataset that contains images with different light conditions. The study also looks at persistence in recognition across frames in video data and a detailed description of the dataset used to train the evaluated models. Finally, the paper also goes through a number of scenarios that applies the results obtained in this study to ITS systems that use ip camera feeds.

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1. Introduction

One of the uses of Computer Vision (CV) and Artificial Intelligence (AI) is in conjunction with the areas of traffic management and Intelligent Transport Systems (ITS). There is already a large selection of different algorithms and

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intelligent models that are used to count cars, predict traffic flow, predict vehicle speed as well as identify dangerous drivers [5]. Notwithstanding the challenges faced when developing these transport systems, there are already a number of models that are considered state of the art. These models use a range of features to output results, including, vehicle size, colour and GPS location. These features and the process of selecting the best approach provides an opportunity to study the effect of applying object detection models to different datasets and scenarios. Thus, the primary contribution of this paper is not to develop a new pipeline for vehicle detection, but, to develop a methodology that allows transport experts to evaluate and find the best models for their particular Intelligent Transport System needs. In addition, this paper also focuses on feeds obtained from live data mined over the internet. In fact, apart from the standard dataset used for the evaluation of this study, we introduce a new dataset in section 3.2 made up of live footage captured through IP cameras. This dataset offers a new set of challenges in itself as the video feed is of low quality. When developing ITS the approaches described in [16] initially create isolated cases where the individual traffic control models work. For example, finding the best camera angle to capture incoming traffic and increase detection accuracy. Additionally, vehicle detection is improved by adding light fixtures and other video enhancing tools to optimise visibility. This process can be time-consuming and not always feasible. Thus, one of the main motivations of this study was to evaluate the different state of the art object detection models on datasets that contain low-quality footage mined over the internet. This is done in order to introduce a more effective way of developing ITS systems that use vehicle detection algorithms and models that do not need custom implementations or a lot of resources to deploy. The evaluation in this paper evaluates vision models that are used for vehicle detection. As previously mentioned these algorithms are often used in different context when building ITS systems. This paper is split into four different sections, the background section identifies the current state of the art approaches to vehicle detection and delves into the configuration of these models. This section is followed with the Methodology that expands on the evaluation metric used, a detailed explanation of the datasets and setup. The third section goes into detection accuracy results for both datasets followed by a discussion that expands on possible usage for the results obtained and which models might better fit different ITS applications. A final conclusion summarises the results obtained and future work in the area.

2. Background

Deep learning has become a state of the art approach to solving machine learning problems given how effective these models are when successfully applied to various fields of study such as speech recognition and computer vision. Machine learning is a field of study comprised of a collection of statistical models that are trained on datasets made up of different features in order to, classify or predict information [2]. For example, a model trained upon weather information would be able to predict the weather for a given date [4]. This process is straightforward but requires fine tuning in terms of data as well as network (model) configuration. Furthermore, with the advent of big data, companies such as Google, Microsoft and Apple that have access to large volumes of data have consistently pushed the field of Deep Learning and have applied it to well-known systems such as Siri for Apple and Google Translate for Google. Deep Learning is not a new concept [11] it has gained popularity in recent years due to advancement in technology. Processing units such as GPU have in the past years become cheaper coupled with the significant increase in processing power of these chips has paved the way for more research in Deep Learning technologies [3]. Deep Learning Models are a set of techniques based on neural networks that exploit current technology to create network configurations built using a large amount of layers as well as trained upon big data. This leads to the deep learning models ability to exploit this architecture for use in unsupervised learning and pattern classification. Thus, significantly increasing the accuracy output of the models compared to their more shallow implementations [21].

2.1. Convolutional Neural Networks for Object Detection

Convolutional Neural Networks (CNN) is a type of feedforward neural network model. Variations of this network have been successfully applied to a number of different computer vision problems. CNNs use the concept of convolution in order to create an architecture using several layers of convolution and nonlinear activation functions [9] [8]. One of the earliest convolutional networks was pioneered by Yann LeCun in 1990 [12]. The resulting architecture called LeNet was used for character recognition for zip codes and numerical digits. What makes convolutional networks attractive is the fact that no features apart from the images are used when training the network. A property that

make CNN stand out with respect to other neural network model's is it's ability to process and find patterns in images [10]. There are a number of different CNN architectures used for object detection. A distinction that is important to note is that there is a difference between network configuration, that is, the number and type of layers used and the network architecture when dealing with object/vehicle detection models. The latter, is usually comprised of a number of CNNs as well as other Machine Learning models to increase detection accuracy and speed. In the following sections, we explore a number of different state-of-the-art models used in object detection.

2.2. You Only Look Once

Most object detection models divide images into regions of interests (ROI) or segments. A detection algorithm is then applied to these ROI/segments in order to classify any object or part of object found. The You Only Look Once (YOLO) model on the other hand applies a single neural network to a whole image [17]. It is then the job of the network itself to divide the image into classified segments and ROI. Another step is then applied by the model to sum the ROI with the same label to finally output the detected object label and location in the image as seen in Figure 1. This significant change in procedure allows the network to detect and classify images at extremely high speeds allowing for real time image detection [18]. The only problem, with this network is that it does not handle very small object well due to the fact that the network attempts to output detection results at one go. The latest version of YOLO on the other hand, manages to more accurately detect smaller objects due to a number of classification steps introduced in the network [19]. The most salient feature of v3 is that it makes detections at three different scales. The only downside to this is a slight reduction in processing speed in fact it is about 15 fps slower than YOLOv2.0.

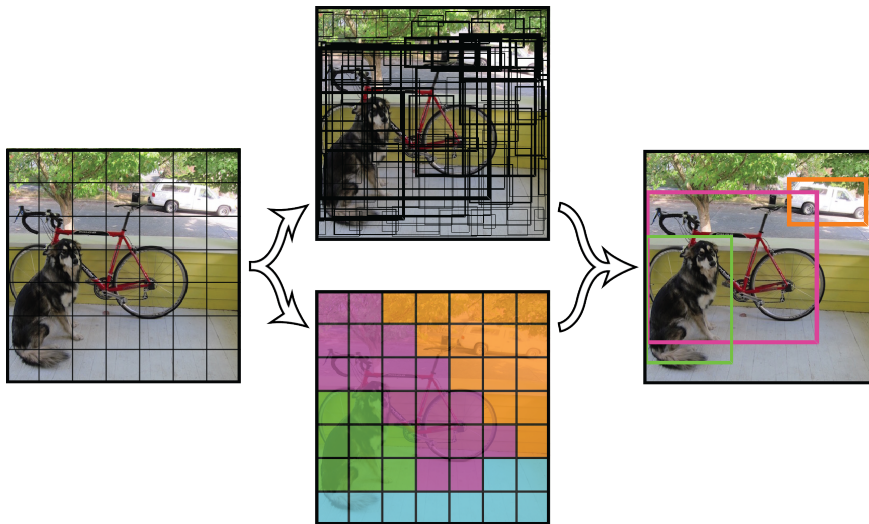


Fig. 1. A representation of how YOLO applies prediction on a single network and how final classification is realised from the amalgamation of the various detected segments.

2.3. RetinaNet

The RetinaNet model implements a similar algorithm to the YOLO detection model. In both cases the models apply a neural network on a single image. These type of detection networks referred to as single stage detection models tend to fail with respect to two stage detectors in terms of detection accuracy. This is mostly due to extreme class in balance encountered when training [14]. The authors of the RetinaNet model manage to solve this issue by applying a focal loss. Focal loss is the reshaping of cross entropy loss such that it down-weights the loss assigned to well-classified examples. The novel focal loss focuses training on a sparse set of hard examples and prevents the vast number of easy negatives from overwhelming the detector during training. RetinaNet also manages to compare around 100,000 different segments for one image in contrast to models such as YOLO that classifies between 98 to 2000 segments depending on the version. In addition, as shown in Figure 2 this model uses ResNet for deep feature extraction as

well as a Feature Pyramid Network (FPN) [13] on top of the ResNet to build a rich feature set that is able to discern between different image patterns and correctly classify multiple objects.

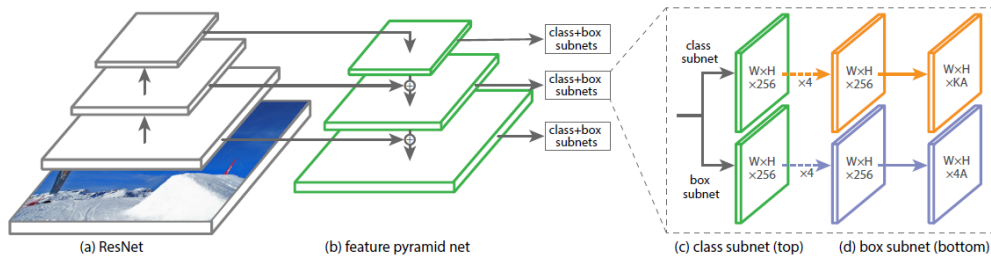


Fig. 2. The RetinaNet network architecture uses a Feature Pyramid Network (FPN) backbone on top of a feedforward ResNet architecture [14]

2.4. Region Based Convolutional Neural Network

The final detection model architecture evaluated in this study is the Region Based Convolutional Neural Network (RCNN). Unlike, YOLO and Retinanet, RCNN splits the detection process into two separate stages. The first stage evaluates an image in order to extract possible ROI. In the first version of the RCNN model [7] the number of extracted ROI amount to 2000 regions. A CNN is then applied on each ROI as a feature extractor in combination with a Support Vector Machine (SVM) as the classification network as shown in Figure 3. Additionally, the algorithm also outputs four different dimensions describing the presence of the detected object in the ROI. Thus, managing to localise the object better and find the border of the detected object. An important feature for Autonomous Vehicle (AV) systems were the boundary of incoming cars and traffic is extremely important. The RCNN architecture has improved over the past four years with the latest version introducing two different processes to the original RCNN architecture [20]. The ROI extracted in the initial stage was done through a greedy search. Faster RCNN applies a pre-processing step that applies convolution to the whole image, followed by a network that is trained to find ROI. The latter step substantially reduces computational time and improves upon the accuracy of the model [6].

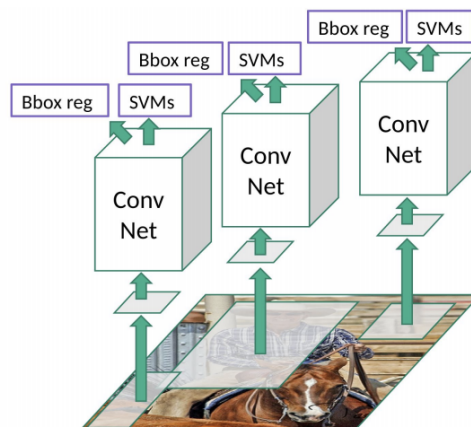


Fig. 3. Process diagram showcasing the breakdown of an image into segments and final detection for an RCNN network [7]

3. Methodology

3.1. Evaluation Methodology

The evaluation was conducted by first building a simple pipeline to convert the video clips into separate frames. Each video frame was individually annotated with, the number of vehicles in the frame, position of vehicles, type of vehicle (if available). A selection of consequent frames were selected upon two different criteria. The first criteria looked for difficulty based on occlusion (vehicles occluded each other), the second criteria were based upon difficulty due to weather or light conditions. The object detection models were then applied on the datasets and the following metrics were measured:

- Detection accuracy
- Number of evaluated images per second (FPS)

In addition, all models are trained on the Common Objects in Context (COCO) dataset [15]. The dataset is made up of 123,287 images and contains 886,284 instances of 81 different category of objects. This dataset as it is a standard detection dataset used in a number of different evaluations [1]. This step also ensures uniformity across training. Although not a transport detection network in itself the COCO dataset contains numerous examples of vehicles split into cars, trucks, buses, bikes and motorcycles as shown in Figure 4. The architectures identified for testing include YOLOv3, Faster RCNN and RetinaNet.



Fig. 4. a,c,b,d are a sample of vehicle detection images found in the COCO dataset. The coloured shapes mask the edge of the vehicles. This is used both for training as well as testing to measure the accuracy of the detection model.

3.2. Setup

The evaluation process undertaken in this study takes into consideration the speed of detection. Thus, it is also important to go through the setup of the machine used for evaluation:

- CPU: Intel Core i7-8750h CPU 2.20GHz
- RAM: 32.0GB
- GPU: GeForce GTX 1050 Ti
- OS: 64-Bit OS Windows 10

3.3. UA-DETRAC Dataset

UA-DETRAC [22] is a challenging real-world multi-object detection and multi-object tracking benchmark. The dataset consists of 10 hours of video footage. The video is captured with a Canon EOS 550D camera at 24 different locations at Beijing and Tianjin in China as seen in Figure 6. Each video is recorded at 25 frames per seconds (FPS), with a resolution of 960x540 pixels. There are more than 140 thousand frames in the UA-DETRAC dataset and 8250 vehicles that are manually annotated, leading to a total of 1.21 million labelled bounding boxes of objects.



Fig. 5. Sample images taken from the UA-DETRAC dataset

3.4. GFRT Dataset

The GFRT (Gozo ferry road transport) dataset is a unique dataset based upon the IP camera capture feeds mined from (Web). The dataset is made up of over 20,000 frame images of 1 min clips taken from 5 different ip cameras across the same road network at different times during the day. This challenging dataset contains 640x320 pixel images under sometimes extreme light in variance conditions. The dataset has been physically annotated by the authors and will be released online later on during the progression of the current research.

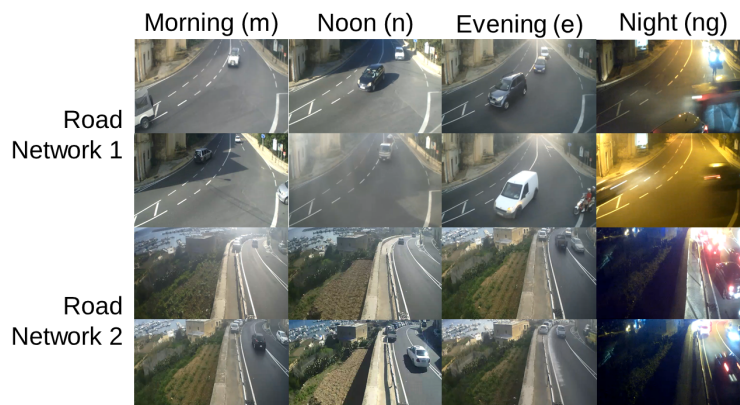


Fig. 6. Sample images taken from the GFRT dataset made up of traffic captured at different times during the day

4. Results

Table 1 represents the results comparing mean average precision (mAP) [23] values and FPS obtained using three different models and applied to two different datasets. Although the detection accuracy is not impressive on its own, one must keep in mind that the dataset chosen for training is not fine tuned on the dataset itself. In addition, we also found that given that the models were trained on the COCO dataset which includes high resolution images the mAP for the GFRT was impacted as the quality of the images supplied was not as good. This meant that in some cases object were incorrectly misclassified due to the resolution difference. As further discussed in the following section most of the ITS apply detection models on video feeds. This means, that although a vehicle might not be detected in 1 frame it can still be detected in other frames as it changes angle or increases in size, thus, increasing overall robustness of the system.

Table 1. Vehicle detection accuracy results

Object Detection Model	Dataset	mAP	FPS
YOLOv3-608	UA-DETRAC	60.8	12
YOLOv3-608	GFRT	54.3	8.22
YOLOv3-tiny	UA-DETRAC	25.8	120
YOLOv3-tiny	GFRT	18.9	144
Retinanet-101-800	UA-DETRAC	61.2	0.2
Retinanet-101-800	GFRT	59.5	1
RCNN	UA-DETRAC	58.4	2
RCNN	GFRT	57.8	3.3

5. Discussion

When developing ITS different use cases require fine tuning in various different aspects of the system. Vehicle detection is used by ITS that process camera feeds to process traffic information visually. These systems use techniques that calculate traffic flow, vehicle speeds as well as tracking of dangerous drivers. If the ITS aims to operate control structures such as traffic lights that change value depending on traffic flow, then, based upon the results and study conducted on this research YOLOv3 gives the best results. This is due to the fact that such a system would require a ip camera footage to be processed in real time but still remain relatively accurate. On the other hand, if traffic flow is needed for training other machine learning models, the, mAP is more important and Retinanet would in that case be the best option. YOLOv3.0 obtained the highest FPS but it also had the lowest mAP. In the case of areas with heavy traffic mAP might not be that important especially if the tracking process results in a workable system. RCNN provided the most balanced result with high accuracy to frame-rate ratio. Finally, if the setup is upgraded to the latest hardware FPS as well as accuracy would increase. For example, on the latest benchmarks YOLOv3.0 achieved an impressive FPS of 220 [19].

6. Conclusion

In this paper, we presented a methodology for evaluating vehicle detection models for intelligent transport systems. The models were applied to two different datasets. An initial dataset used for vehicle detection as well as new dataset used for the first time in this study. Finally, the results show that YOLOv3.0 and Faster RCNN are the most balanced models when comparing mAP and FPS. Further research needs to be done to measure the affect that the detection accuracy has on vehicle tracking models as well as possible pre-processing techniques that can be used to improve image quality when working with low quality ip camera feeds.

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