Data-driven vehicle speed detection from synthetic driving simulator images

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Abstract—Despite all the challenges and limitations, vision-based vehicle speed detection is gaining research interest due to its great potential benefits such as cost reduction, and enhanced additional functions. As stated in a recent survey [1], the use of learning-based approaches to address this problem is still in its infancy. One of the main difficulties is the need for a large amount of data, which must contain the input sequences and, more importantly, the output values corresponding to the actual speed of the vehicles. Data collection in this context requires a complex and costly setup to capture the images from the camera synchronized with a high precision speed sensor to generate the ground truth speed values. In this paper we explore, for the first time, the use of synthetic images generated from a driving simulator (e.g., CARLA) to address speed detection using a learning-based approach. We simulate a virtual camera placed over a stretch of road, and generate thousands of images with variability corresponding to multiple speeds, different vehicle types and colors, and lighting and weather conditions. Two different approaches to map the sequence of images to an output speed (regression) are studied, including CNN-GRU and 3D-CNN. We present preliminary results that support the high potential of this approach to address vehicle speed detection.

I. INTRODUCTION

Accurate and efficient detection of vehicle speed from external systems is a well-established area of research and development, which in recent years is attracting more research attention due to the impact these systems have on road safety. Speed enforcement is a key road safety measure that directly leads to a reduction in accidents [2]. Indeed, in the vicinity of speed cameras the reduction of speeding vehicles and crashes can reach up to 35% and 25% respectively [3]. In addition, it has been proven that, the higher the intensity of enforcement, the greater the reduction of accidents [4].

The requirements for accuracy and robustness in vehicle speed measurement for speed enforcement are very demanding [5]. Thus, the most common sensors used for speed estimation are based on high-accuracy, high-cost range sensors, such as radar and laser, and, in some cases, on sensors in the pavement embedded in pairs under the road surface. The use of cameras has rarely been proposed for speed enforcement. They usually play a secondary role in capturing human-understandable scene information, allowing visual identification of vehicles and serving as evidence when the speed limit is violated.

However, the potential benefits in terms of cost reduction and enhanced functionality, as well as recent advances in the field of computer vision have led to a significant increase in the number of works using vision as the sole mechanism for measuring vehicle speed [1]. This a challenging problem due to the discrete nature of video sensors, in which the accuracy of the representation decreases proportionally to the square of the distance, and the worsening of performance in adverse weather conditions. An additional difficulty is the limited availability of data in real environments that allow the deployment of learning-based approaches. Data collection in this domain requires a complex, and costly, setup to capture the images from the cameras synchronized with some high precision speed sensor to generate the ground truth speed values. The number of datasets with this type of information is still very limited, and this implies that the use of data-driven strategies is far from being consolidated in this application context.

In this paper, we study, for the first time, the use of synthetic sequences generated from a driving simulator to address vehicle speed detection using a learning-based approach. We present a highly realistic synthetic dataset with sequences generated from a virtual camera placed over a stretch of road, for the development and evaluation of vehicle speed detection methods. We use the open-source CARLA simulator for autonomous driving research [6] which allows the variation of multiple parameters, including the road layout, vehicle dynamics, different types of vehicle and colors, as well as multiple lighting and weather conditions. We then address the vehicle speed detection problem as a sequence-
to-sequence regression problem [7] using two different methods: CNN-GRU [8] and 3D-CNN [9]. An overview of our approach is depicted in Fig. 1. We present preliminary results with only one virtual camera, which support the proposed methodology and validates the usefulness of our synthetic vehicle speed detection dataset.

II. Related Work

As stated in a recent survey [1], despite the fact that we can find hundreds of works focusing on vision-based vehicle speed detection, the problem is still in a moderate level of maturity. Multiple issues remain open, such as robustness in difficult lighting and weather conditions, sub-optimal system settings resulting in very high meter-to-pixel ratios, the lack of well-established datasets that allow to compare the performance of different methods, and the still small number of data-driven approaches which are well consolidated in other computer vision areas.

In this paper, we focus on learning-based methods, so we only analyze this type of approaches in the state-of-the-art presented. We refer to [1] for a comprehensive and detailed overview of the vehicle detection problem from non-learning based approaches, including a complete taxonomy that categorizes all the stages involved.

A. Data-driven approaches

Concerning the estimation of vehicle speed using learning-based methods, only a few works can be found in the available literature. In [10], the authors propose the use of a CNN to estimate the mean speed of all vehicles using two consecutive images from a top view of a two-lane road segment. They propose to use two types of datasets, one using images from a long-distance video camera over a stretch of road, and the other using a synthetic set generated by a cycle-consistent adversarial network (Cycle-GAN) that converts animation images into realistic photos. Although this approach cannot be applied for accurate detection of the speed of each individual vehicle, and despite the limitations and fluctuations of the adversarial network to generate realistic images, the idea of using synthesized images to train a CNN model to estimate the average speed of traffic, which is then tested on real images, is worth mentioning. In [11], average traffic speed estimation is addressed as a video action recognition problem using 3D CNNs. They propose to concatenate RGB and optical flow images. They found that optical flow was crucial information for the vehicle speed estimation problem. However, as stated in the paper, the main limitation of the proposed model was the lack of data which could lead to overfitting. Finally, in [12] a Modular Neural Network (MNN) architecture is presented to perform joint vehicle type classification and speed detection.

In all these cases, the input sequence corresponds to a road section with multiple lanes and vehicles, making them more suitable for traffic speed detection. The question is how to extend these approaches to perform individual vehicle speed detection. As it happens when applying video action recognition approaches for the classification of vehicle lane changes [13], it could be necessary to generate regions of interests (ROIs) with sufficient spatio-temporal information to distinguish different speeds for different types of vehicles and scenarios. This problem can also be mitigated by using a camera setting with a very low meter-pixel ratio focusing on a single road lane.

B. Datasets

As described in [1], we can only find two datasets with speed ground truth available. First, we have the BrnoComp-Speed benchmark [14], which contains 21 sequences at a resolution of 1920 × 1080 pixels at 50fps, each sequence of 1 hour duration, including almost 21K tagged vehicles. Speed ground truth is provided using a laser-based light barrier system. The sequences were recorded in real traffic conditions in highway scenarios. The images cover between 2 and 3 lanes, in road segments of several dozens of meters. Therefore, the images have a high-medium meter-to-pixel ratio. Second, we have the UTFPR dataset [15] which contains up to 5 hours of sequences of images from a urban environment (speed limit at 60 km/h), 1920 × 1080 of pixel resolution at 30fps, recorded from one camera covering up to 3 lanes, and includes different weather conditions. The ground truth speeds are obtained using inductive loop detectors. The camera position has a considerable pitch, which produces a favorable medium-low meter-to-pixel ratio.

These datasets contain valuable information for the purpose of vehicle speed detection, as they contain real data. However, they lack the versatility that is available in a simulated environment, where we can easily vary the camera parameters, vehicle types, speed range, road layout, lighting and weather conditions, etc. Given that cars are rigid objects, and thanks to the constantly improving visual realism offered by driving simulators, this is undoubtedly a favourable application context where the generation of synthetic sequences for the development and evaluation of different methods, has the greatest potential.

III. Method

This section describes, on the one hand, the process of generating the synthetic dataset and, on the other hand, the CNN-based regression models used for speed estimation.

A. Dataset construction

The synthetic dataset was generated using the CARLA driving simulator [6] as it features a high degree of visual realism in all its scenarios, thanks to the UnrealEngine graphics engine. It allows to use a wide variety of vehicles, weather and lighting conditions, as well as the placement and orientation of one or multiple cameras. All the parameters that can be adapted to generate the synthetic vehicle speed detection dataset are depicted in Fig. 2.

We construct synthetic temporal sequences using one fixed camera at 80 FPS with Full HD format (1920x1080), located at a height of 3 meters, with a pitch angle of 45 degrees, and with the Z-axis parallel to the direction of travel of the vehicles. A straight road section has been selected from the
map labeled as “Town01”. Up to 27 different vehicles were used including multiple car makes and models (e.g., Audi e-tron, Citroën C3, Toyota Prius, etc.), trucks, motorbikes, and bikes, with different colors.

Multiple lighting and weather conditions have been simulated. The solar elevation angle was discretised to two positions Noon (75°) and Sunset (15°). The precipitation percentage was discretised to values of (0, 15, 30 and 60), and the precipitation deposition percentage on the surface was discretised to (0, 50, 100). Although the simulator also allows the modification of other parameters, such as cloudiness or ambient fog, they have not been taken into account in this preliminary study.

The number of images generated in each sequence will depend on the speed of the vehicle. In this case, preliminarily, the sequences are generated with constant speeds (zero acceleration). The (initial) speeds are generated randomly according to the following equation:

\[
\text{Speed}(i) = 8.33 + X(i) \cdot 19.44
\]  

where \(i\) is the episode, and \(X(i)\) is a randomly selected number from a uniform distribution between 0 and 1. In this way, speeds between 8.3 and 27.7 m/s (≈ 30 and 100 km/h) are obtained. The obtained speed distribution is depicted in Fig. 3. This range of speeds has been preliminarily selected in order to validate the methodology for urban environments. For the case of highway or secondary roads, the maximum speed should be extended, as well as the camera capture FPS.

The generated synthetic vehicle speed detection dataset contains 610 episodes, where each episode is formed of a sequence of images which depend on the speed of the vehicle. Therefore, the dataset contains approximately 60,000 images labelled with vehicle speed, vehicle type and environmental conditions. Fig. 4 shows frame 30 of some of the synthetic episodes.

### B. Sequence-to-Sequence regression

Vehicle speed detection is approached as a regression problem in which the model learns how to map the spatial and temporal relationships of a sequence of images to the corresponding vehicle speed. Two different models are adapted, implemented and validated, which will be described below.

1) 3D CNN: The idea behind the 3D CNN model is to integrate spatial and temporal information into a 4D input tensor, and stack 3D convolutional layers with 3D convolutional filters that implicitly learn spatial and temporal features. This work explains how to perform 3D convolutions, using 3D kernels that are applied to the cube formed by stacking multiple contiguous frames together. Thus, the feature maps in the convolutional layers are connected to multiple contiguous frames in the previous layer, thereby capturing motion information.

In our case, we propose to use 3D convolutional filters within the framework of residual learning. Following the approach proposed in [16], we apply a 3D ResNet18 architecture. Pre-trained models are usually obtained from human action classification datasets such as Kinetics-400 [17], whose spatial and temporal features are very different from those that appear in our scenarios. Therefore we perform training from scratch. The input is a 4D tensor of size \(3 \times N \times W \times H\), being \(N = 16\) the number of stacked frames which are obtained evenly spaced from a fixed time horizon. This implies that slower vehicles do not leave the camera’s field of view, and for faster vehicles, the last images remain with the car having left the field of view (note that, in our preliminary study we consider that a sequence does not contain more than one vehicle).

2) CNN-RNN: VGG16 [18] has been chosen as the CNN feature extractor (i.e. freezing all layers). Using ImageNet
[19] pre-trained weights, the output of the last convolutional layer has been used, with a dimension of $7 \times 7 \times 512$. This feature vector is flattened and used as input to the recurrent model, which is composed by a GRU [20] layer with 50 units, an alternative to LSTM with similar performance and less computation requirements, and a dense layer with one output neuron. The number of timesteps is defined as $N = 32$, corresponding to the features from evenly spaced images from a fixed time horizon (see Fig. 5(b)).

### IV. Experimental Evaluation

#### A. Training parameters

The total episodes recorded in the database are 610, split into 366 (60%), 122 (20%) and 122 (20%) to generate the training, validation and test subsets, respectively.

Adam optimizer and MSE loss are used in both models, with a learning rate of $3 \times 10^{-4}$ in the 3D ResNet case, and $10^{-4}$ in the CNN-GRU. Another difference between both models is in the batch size, and in the number of epochs, being 5 and 100 in the 3D model, and 3 and 150 in the RNN, respectively. Also, in the 3D-CNN model, early stopping is used, with a patience of 7, so the training end in epoch 25/100. To perform some regularization, the output targets are normalized between -1 ($30km/h$) and 1 ($100km/h$).

The 3D CNN has a total of $33,166$M trainable parameters, while the VGG16-GRU has $14,714$M corresponding to the VGG16 pre-trained model and $3,771$M to the trainable GRU architecture.

#### B. Results

The behaviour shown by both network architectures in the training and validation process is shown in Fig. 6. The losses converge rapidly to values below 0.1. The general results are very satisfactory. On the one hand, the architecture based on CNN-GRU presents an average speed error of $0.91m/s$ and the architecture based on 3D-CNN of $0.35m/s$. The two architectures have been compared using the same training, validation and test splits.

Figs. 7 and 8 show the absolute error that the two architectures perform in the speed estimation of each test episode. Fig. 7 combines information on the type of vehicle associated with the episode. With the CNN-GRU architecture, all the errors are below the threshold of $1.5m/s$, with two episodes with errors above $4m/s$ which correspond to two motorbike models (kawasaki.ninja and yamaha.yzf). These are small vehicles where the features generated may not be sufficiently representative. However, the 3D-CNN architecture net shows a stable behaviour, improving the estimation in all episodes concerning the CNN-GRU network, and mitigates the estimation problems found with the recurrent architecture because it obtains estimation errors in motorbikes close to $0.1m/s$.

On the other hand, Fig. 8 integrates information on the environmental conditions associated with each episode. As in the previous case, the errors obtained by the CNN-GRU net are below the $1.5m/s$ threshold, and it is the two episodes studied above that present a higher error. If we analyse the environmental conditions associated with these episodes, Midday_00 and Sunset_30_50, and compare them with the rest of the episodes, we can assert that the error is not related to the simulated lighting conditions. We infer that the error associated with these episodes come from the type of vehicle and the lack performance offered by the CNN-GRU net for these cases. On the other hand, and as in the previous analysis, we the 3D-CNN model provides accurate results robust to environmental conditions variability.

Fig. 9 shows the speed error function of simulated vehicle...
type, as well as the number of times the vehicle type appears in the test episodes (light green box) and average simulated speed for the vehicle in the set of episodes (light pink box) for both models. As in the previous case, in the CNN-GRU model, the error evaluated when the episodes include the aforementioned motorbikes stands out. However, the two error values that rise above the rest have the common factor of simulating the slowest speeds in the set of episodes, i.e., 9.4 m/s and 11.5 m/s. The minimum error is 0.5 m/s, which is linked to audi.etron, nissan.micra and tesla.model3 vehicle models, with simulated speeds between 18 m/s and 19.5 m/s. The 3D-CNN model provides better results, with a maximum error of 1 m/s.

On the other hand, Fig. 10 depicts the absolute error in the speed estimation for the simulated lighting and weather conditions, as well as the number of times simulated (light green box) and the average simulated speed for the vehicle in the set of episodes (light pink box). The CNN-GRU model has a uniform behavior for all simulated environmental conditions. The maximum error is 1.4 m/s, associated with Sunset, precipitation of 30% and precipitation deposit of 50%, which is linked with episodes where the motorbikes were simulated. Again, the 3D-CNN model provides more accurate and robust results in all the study cases, with errors lower than 0.8 m/s.

Finally, we analyze the mean absolute error as a function of the speed (Fig. 11). Counter-intuitively, in both cases, the estimation error does not seem to increase with vehicle speed. The number of samples is still relatively small, and the maximum speed is limited to 100 km/h. Although these preliminary results do not allow us to confirm whether this trend would occur at higher speeds, the fact that the error remains stable in the tests performed is very positive in view of an implementation of the system in real conditions.

In Fig. 12 we present three episodes with three different speeds, in which the errors of both models were less than 0.2 m/s.

V. Conclusions

This paper presents a learning-based accurate vehicle speed detection system using a new synthetic dataset, built by simulating a virtual camera in an autonomous driving simulator (CARLA). Data-driven approaches have so far not been robustly explored due to the difficulty in generating real datasets, with a sufficient number of vehicle sequences, with real speed values. The main contribution of our approach is based on the use, for the first time, of synthetic sequences for the generation of a vehicle speed detection system based on deep learning, with the necessary accuracy for its use as a speed enforcement system. A synthetic dataset with more than 600 episodes has been generated, with a high variability of vehicles, weather and lighting conditions.

Two different methods have been applied to address speed detection as a sequence-to-sequence regression prob-
lem using the synthetic sequences. First, a CNN-RNN model implemented with a VGG16 network to generate features from the images and a GRU layer to integrate temporal information which reports a MAE of 0.91 m/s (3.27 kmh). Second, a model based on 3D convolutions, implemented using a 3D ResNet, which provides a MAE of 0.35 m/s (1.26 kmh). These results, while still preliminary, are within the limits required by certification agencies, and validate our methodology as a basis for the development of accurate vision-based speed enforcement systems.

However, this work has several limitations that need to be addressed in future work. For example, the range of speeds to be studied must be increased significantly. The dataset must be augmented with data from different cameras with variability in position and orientation, trying to address the problem independently of the camera perspective. Finally, the sim-to-real gap must be addressed and our methodology must be validated with real data sequences.

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