Vehicle Tracking and Speed Estimation from Traffic Videos

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Abstract

The rapid recent advancements in the computation ability of everyday computers have made it possible to widely apply deep learning methods to the analysis of traffic surveillance videos. Traffic flow prediction, anomaly detection, vehicle re-identification, and vehicle tracking are basic components in traffic analysis. Among these applications, traffic flow prediction, or vehicle speed estimation, is one of the most important research topics of recent years. Good solutions to this problem could prevent traffic collisions and help improve road planning by better estimating transit demand. In the 2018 NVIDIA AI City Challenge, we combine modern deep learning models with classic computer vision approaches to propose an efficient way to predict vehicle speed. In this paper, we introduce some state-of-the-art approaches in vehicle speed estimation, vehicle detection, and object tracking, as well as our solution for Track 1 of the Challenge.

1. Introduction

The continuously increasing number of on-road vehicles has put a lot of pressure on road capacity and infrastructure, making traffic management difficult and giving way to problems like congestion, collisions, and air pollution, among others. These problems have significant impact on our daily lives. A robust and efficient traffic management system is required to reduce their effect. A large amount of traffic data is generated daily. Traffic data contains information related to traffic flow, distribution, pattern, and collisions, which can be used to solve various traffic related issues. The volume and distribution of traffic can be used to build appropriate structural and geometric designs for road segments. Traffic collisions can be analyzed to see the correlation of traffic volume and number and severity of collisions, which in turn can help to investigate and assess collision risks. Apart from these problems related to vehicle traffic, the data can also help in studies related to the reduction of environment pollution and fuel consumption. Also, various statistical parameters, such as the average number of vehicles on the road at a certain time, and the state of congestion, can be studied, which can provide some information for managing the highway [17].

To address these pressing issues, NVIDIA initiated a series of challenges aimed at the intersection of Artificial Intelligence and Smart City. The first AI City Challenge, organized in 2017, focused on object detection, localization, and classifications. The 2018 AI City Challenge continues to promote deep learning and computer vision approaches to help analyze urban traffic videos, and finally improve traffic conditions and prevent traffic collisions. This workshop especially focuses on solving serious problems related to urban traffic. Specifically, the challenge is comprised of three tracks: Track1 (Traffic Flow Analysis) aims at developing models that can predict the driving speed of vehicles in videos recorded by stationary cameras on highways or at intersections. Track2 (Anomaly Detection) focuses on detecting driving anomalies, such as stalled vehicles or car accidents, in the videos. Track3 (Multi-camera Vehicle Detection and Re-identification) aims to detect and track all vehicles in a set of videos which appear in each of a subset of the videos recorded at different locations within the city.

In this paper, we propose a formulation to solve Track1. Our model relies heavily on vehicle detection and tracking. In this Challenge, however, it is hard to train a vehicle detection model from scratch since no labeled data is provided. Instead, we leverage transfer learning and perform inference on our dataset using the 3D Deformable model [16] for vehicle detection. As an alternative to the 3D Deformable model, we considered the model by Bhandary et al. [2], which obtained similar performance in the 2017 challenge. To be able to compare these two models on the target reference data, we extract all frames from one of the Track 1 videos and measure the models' performance on the frames, comparing the vehicle detection performance as measured by mean Average Precision (mAP). The experi-

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ment shows that the 3D Deformable model [16] achieves 74% mAP, which is higher than the model of Bhandary et al. [2].

The methodology of our tracker is *detect-then-track*. The performance of the tracker is thus highly dependent on the accuracy of the detection. For each frame, we extract salient features from the detected vehicles and then identify them in the next frame. The change of in-frame location of these features contribute the necessary information for estimating the vehicle's speed.

2. Related Works

Vehicle tracking is required in order to build a robust vehicle speed estimation model. Many methods have been developed that use classic computer vision and machine learning approaches for object tracking. Kale et al. (2015) [11] utilized a classic optical-flow algorithm as well as motion vector estimation to solve the object tracking problems. They proposed a track-by-detect approach, where detection was done by using an optical-flow algorithm and speed estimation was handled by motion vector estimation. Geist et al. (2009) [8] contributed a reinforcement learning-based framework, combined with a Kalman Filter to address the non-stationary environment. The paper proposes that tracking objects in the video can be viewed as the problem of predicting the location of the bounding box of that targeted object at each frame. Zhang et al. (2017) [22] developed a recurrent convolutional neural network model trained with a Reinforcement Learning algorithm. Faragher (2012) presented a simple and detailed explanation of Kalman Filters [6]. The paper explains the assumption behind Kalman Filters and derives the process of modeling a tracking problem mathematically, step by step. Brasnett et al. (2005) proposed an approach to track objects by combining features with a particle filtering algorithm, solving nonlinear, non-Gaussian tracking problems.

Many research studies have also been conducted in the field of vehicle speed detection with various approaches. Rad et al. (2010) [15] has proposed an approach involving the comparison of the vehicle position between the current frame and the previous frame to predict traffic speed from digital video captured with a stationary camera. The camera calibration was done by applying geometrical equations. The system designed by Rad et al. has the potential to be extended to other application domains and has an average error of ± 7 km/h for the detected vehicle speed. Ferrier et al. (1994) [7] used the motion parameters in the image, along with information on the projection between the ground plane and the image plane, to obtain various metrics, including vehicle speed, using real-time tracking techniques. They have also used scene specific tuning of the dynamics for more accurate prediction of target location by the tracker. Yamazaki et al. (2008) [21] have used digital aerial images to detect vehicle speed by extracting the vehicles and shadows from two consecutive images. The speed is detected by linking the corresponding vehicles from these images based on their distance, order and size and then using distance between corresponding vehicles and time lag. Wu et al. (2009) [20] have utilized mapping of the coordinates in the image domain into the real-world domain. Liu and Yamazaki have used a pair of QuickBird panchromatic and multi-spectral images for speed detection [12]. Gerát et al. [9] used the combination of Kalman filters and optical-flow approaches to estimate speeds. The former is helpful in avoiding the problem of temporary occlusions, while the latter provides more accurate speed delivery.

Wang [19] presented an approach based on moving target detection in a video by mapping the relation between pixel distance and actual distance. In this algorithm, three-frame differencing and background differencing were used to extract features from moving vehicles. Then, tracking and positioning was done using vehicle centroid feature extraction.

3. Dataset

Unlike the 2017 AI City Challenge, which focused on applying supervised models to traffic related problems and thus included a large collaborative annotation effort for the dataset, this year the challenge focused more on transfer learning approaches and does not include any annotations. The dataset available has been captured by stationary cameras located at urban intersections and freeways. Figure 1 shows a sample of the dataset recorded at an intersection and a highway. Following are details of the dataset:

- The Track 1 dataset contains 27 one-minute 1080p videos (1920x1080) recorded at 30 frames per seconds (fps). Those videos are captured at 4 different locations, locations 1 and 2 being highway and 3 and 4 intersection locations, respectively.
- The Track 2 dataset involves 100 videos, each approximately 15 minutes long, recorded at 800x410 resolution and 30 fps.
- The Track 3 dataset has 15 videos of 1080p resolution recorded at 30 fps, in four different locations. Each video is 0.5 to 1.5 hours long.

3.1. Geometry Information & Speed Limit

The maximum speed of each road segment can be inferred from the descriptions in the meta-data files associated with each video. Because of the orientation of the cameras, traffic is only recorded from two opposite directions at location 1 and location 2; at locations 3 and 4, the camera captures intersection traffic from two cross-roads and thus

Figure 1. A sample of images captured at traffic intersections and highway.

Table 1. Geometry & speed limit data for track 1.

Loc.	Latitude	Longitude	Direction	Speed
1	37.316788	-121.950242	E $\rightarrow$ W	65 MPG
2	37.330574	-122.014273	NW $\rightarrow$ SE	65 MPG
3	37.326776	-121.965343	NW $\rightarrow$ SE	45 MPG
3	37.326776	-121.965343	NE $\rightarrow$ SW	35 MPG
4	37.323140	-121.950852	N $\rightarrow$ S	35 MPG
4	37.323140	-121.950852	E $\rightarrow$ W	35 MPG

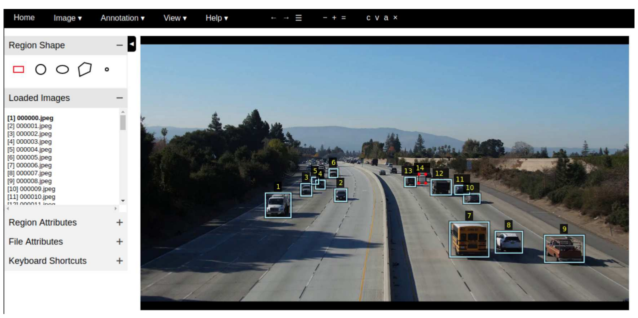


Figure 2. VGG image annotation tool.

four different directions. Table 1 summarizes the location and speed limit information for each video for track 1, for one direction of each road. The opposite direction has the same posted speed limit.

3.2. Annotation tool

We generated some ground-truth data to evaluate different models for vehicle detection. The tool we used to annotate data is the VGG Image Annotator(VIA) [5]. This tool is browser-based and supports advanced functionality, such as copy/paste of a bounding box. Since the frames we annotated are sequential and the position of vehicles changes little from frame to frame, VGG is an easy tool to use to label challenge data. Figure 2 shows a screen-shot of the VGG tool.

4. Methodology

In this section, we introduce our methods for tracking vehicles in traffic videos and estimating their speed. Our method takes a *detect-then-track* approach and can use object detections from any vehicle detection algorithm as input. We will discuss, in turn, our strategy for ensuring quality detections, identifying vehicle tracks, and estimating their speed.

4.1. Vehicle Detection

Given the fact that the 2018 AI City Challenge dataset did not provide any ground-truth detection or tracking annotations, we were not able to train a vehicle detection model specific to this dataset. Instead, we rely on *transfer learning*, taking advantage of state-of-the-art deep learning models that have been previously trained for this task. Specifically, the videos in Tracks 1 and 3 of the dataset are similar in quality and scope to videos used for the object detection, localization, and classification task of the 2017 AI City Challenge [14]. As such, we have chosen to rely on the top-2 best performing models from that challenge, the 3D Deformable model by Tang et al. [16] and our lab's submission to that challenge, the model by Bhandary et al. [2]. Both models provide as output, for each frame, a series of bounding-boxes believed to contain an object of interest, the class of that object, and a confidence score. The 2017 challenge sought to localize and classify objects in 14 categories, including *car*, *suv*, *smalltruck*, *mediumtruck*, *largetruck*, *pedestrian*, *bus*, *van*, *groupofpeople*, *bicycle*, *motorcycle*, *trafficsignal-green*, *trafficsignal-yellow*, and *trafficsignal-red*. In order to maximize the utility of the detections we will provide as input to our algorithm, we filter the detector output as follows:

- Remove detections with a confidence less than some threshold α.
- Remove detections for non-vehicle classes, keeping only those for the car, suv, smalltruck, mediumtruck, largetruck, bus, van, bicycle, and motorcycle classes.
- Filter bounding boxes within the same frame that have an overlap, measured by the Intersection-over-Union (IOU) score, of at least some threshold β. Detections are filtered while traversing the frame in a left-right top-down order when the IOU of the detection with an already selected bounding box is greater than β.

4.2. Vehicle Tracking

Our vehicle tracking algorithm relies on localization results from the vehicle detection methods described in Section 4.1, which are enhanced with optical-flow based features to provide robust vehicle trajectories.

4.2.1 Tracking-by-Detection

Given the fact that the input footage was at 1080p resolution and 30 fps, objects move few pixels from one frame to the next. We thus define an efficient algorithm to define initial object tracks based solely on the overlap of detected object bounding boxes in consecutive frames. Specifically, for each object in a frame, in decreasing order of detection confidence, we assign the ID of the not already assigned object with the highest IOU score in the previous h frames, as long as that score is above a minimum threshold i.

Tracking-by-detection works well in practice for our setting, but is prone to a high rate of ID changes when the detector fails to localize an object for more than h frames. Moreover, detectors often provide loose localization bounding boxes around the detected objects, which shift several pixels around the object from frame to frame, making speed estimation from bounding boxes inaccurate. Figure 3 shows a couple examples of detection errors, including a tree and buildings being detected as vehicles and wide margins between the bounding-box and the detected object in some cases.

4.2.2 Tracking-by-Flow

We improve the simple detection-only based tracking by computing the optical flow for a sparse set of detected object features, namely Shi-Tomasi corners [18], using the iterative Lucas-Kanade method with pyramids devised by Bouguet [3, 13]. For the purpose of the flow estimation, *corners* are small $u \times v$ regions in the image with large variation in intensity in all directions. The Shi-Tomasi corner detector is an improvement over the Harris corner detector [10], which finds potential corners by computing the eigenvalues λ_1 and λ_2 of the matrix

$$M = \sum_{x,y} w(x,y) \begin{bmatrix} \mathbf{I}_x\mathbf{I}_x & \mathbf{I}_x\mathbf{I}_y \\ \mathbf{I}_x\mathbf{I}_y & \mathbf{I}_y\mathbf{I}_y \end{bmatrix},$$

where $\mathbf{I}_x$ and $\mathbf{I}_y$ are the frame derivatives in the x and y direction, respectively, and w is a function weighing the contribution of derivative windows in the composition. While Harris considered windows as potentially containing a corner if

$$R_1 = \lambda_1\lambda_2 - k(\lambda_1 + \lambda_2)^2$$

was above some threshold, Shi and Tomasi showed that windows where $R_2 = \min(\lambda_1,\ \lambda_2)$ was significantly high were more likely to contain distinctive corner features. In our method, we further limit chosen corner points in a frame to only those within the area of at least one bounding box provided by our vehicle detector, which we have not filtered in previous steps.

The Lucas-Kanade method assumes that the intensity of a chosen point does not change from one frame to the next and that the point and its neighbors have similar motion. It estimates this motion by considering the change in location of the chosen point and its neighbors between the two frames. Our method keeps track, for each corner point associated with a tracked object, of the detected point locations in at most t past frames. The *tracklets* obtained in this way provide a signal for estimating the motion of the vehicles that the corner points represent. Figure 4 shows some examples of tracklets detected in each of the four challenge camera locations.

4.3. Speed Estimation

Our method takes a data-driven approach to estimating the speed of vehicles and relies on several strong assumptions. First, the camera recording traffic should be static, which holds for the 2018 AI City Challenge. Secondly, we assume that the maximum speed limit is known for the road segments captured in the footage and at least one vehicle drives on the segment at that speed. Our algorithm takes as input, for each video, the maximum speed $s_{\max}$ that some vehicle is assumed to drive in the footage and estimates vehicle speeds as a function of their *local movement* and $s_{\max}$. We define the local vehicle movement as a function of the maximum historical corner point movement within the tracklets associated with the vehicle, i.e.,

$$\Delta m = \underset{i}{\texttt{perc}_p} \left(\max_{j=2}^{|T_i|} (\, \|T_i(j) - T_i(j-1)\|_2 \,) \right),$$

where T_i is the ith tracklet detected for the vehicle, $T_i(j)$ is the jth historical point in the tracklet, and $|T_i|$ is the size, or number of points in the tracklet. The $\texttt{perc}$ function computes the pth percentile across the individual tracklet movements. Considering the distribution of tracklet estimated local movements helps filter out some outliers due to incorrect corner point detection in some tracklets.

The relationship between local movement and vehicle movement is not uniform across the frame. Since each camera has a different angle with the roads being captured, in order to normalize object movements, one would have to estimate a 3×4 projection matrix $\mathbf{P}$ by relying on a set of vanishing landmark points and prior knowledge of camera parameters [4]. Instead, since we do not know the camera settings, we approximate the projection by learning a set of functions across horizontal tiles of the input video. Intuitively, cameras are aligned with the horizon. As such, vehicles traversing a frame from top to bottom (or vice-versa) will appear to be moving slower towards the top of the screen, as they reach the horizon, even though they may be driving at a constant speed in reality. On the other hand, vehicles traversing the frame from left to right will have a relatively constant local movement/speed ratio.

For small enough tiles, the change in the relation of local movement to vehicle speed will be negligible. We thus consider a *predicted speed* (PS) model that computes the speed

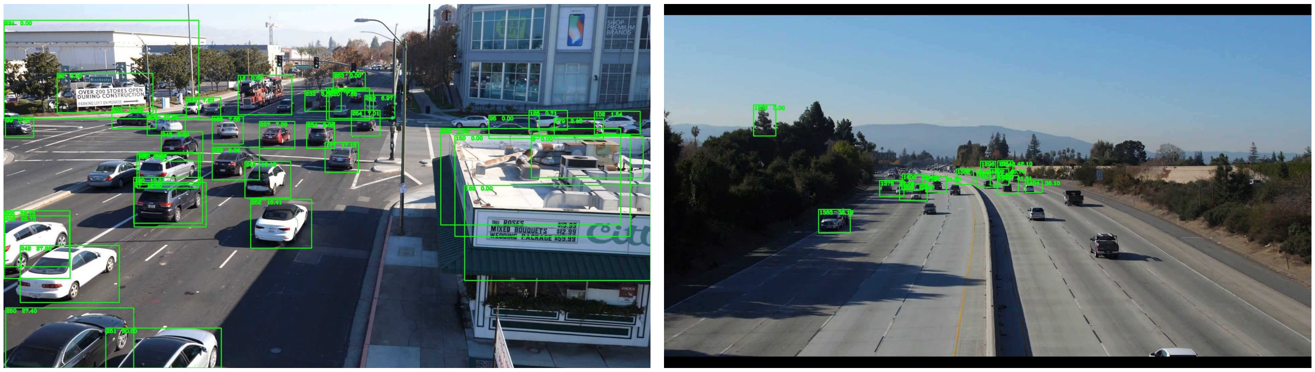


Figure 3. Detection error. (*Best viewed in color*)

Figure 4. Tracklets obtained through optical-flow estimation. (*Best viewed in color*)

of a vehicle, in each tile, as

$$s = \frac{\Delta m}{\max\limits_{T} \Delta m} \times s_{\max},$$

where $\max\limits_{T} \Delta m$ is the maximum local movement in any tracklet of a vehicle passing through the tile within a window Δt of the current vehicle. We further smooth out outliers by considering the maximum estimated vehicle speed over at most h past frames. Finally, we limit estimated speeds within the range $[0,\ s_{\max}]$.

Many of the cars drive at constant speeds through the frame, especially in highway traffic without congestion, as found in Loc 1 and 2 videos of the challenge. We thus consider a second *constant speed* (CS) model, which assigns the input $s_{\max}$ speed to all detected vehicles in the video, after first filtering based on confidence and track overlap.

5. Experiments

In order to choose one of the two detection models we first considered in Section 4.1, we first manually labeled the first 250 frames in video 1 of location 1 as our ground-

Table 2. Detection performance.

Mddel	mAP_0	mAP_1
Bhandary [2]	0.34	0.34
3D Deformable Model [16]	0.28	0.74

truth, used both models to detect vehicles in the video, and then compared the mean Average Precision (mAP) of the two models. For each model, we filtered low-confidence detections with confidence scores α below 0.0 (no filtering) and 0.1, respectively, which we denote in Table 2 by mAP_0 and mAP_1. The results seem to indicate that the 3D Deformable model is superior to the one by Bhandary et al., given proper confidence thresholding. In our Challenge submissions we tested 3D Deformable models with minimum confidence scores α between 0.01 and 0.05.

All experiments were executed on a system equipped with a 5th generation Core i7 2.8 GHz CPU, 16 GB RAM, and an NVIDIA Titan X GPGPU. For each location, we tested maximum speed limits $s_{\max}\pm\{5, 10, 15\}$ miles/hour, given posted speed limits noted in Table 1. For duplicate detection filtering, we used an IOU threshold β of 0.9, During tracklet identification, we considered overlapping detections with minimum IOU 0.7, kept a history of up to $h = 10$ corner points for each tracklet, and estimated local movement from the top $p = 80\%$ tracklet segments.

The 2018 AI City Challenge Track 1 was evaluated based on a composite score, $S1 = DR \times (1 - NRMSE)$, where DR is the vehicle detection rate for the set of ground-truth vehicles, and $NRMSE$ is the $RMSE$ score across all detections of the ground-truth vehicles, normalized via min-max normalization with regards to the $RMSE$ scores of all best solutions of other teams submitting solutions to Track 1. Ground-truth vehicles were driven by NVIDIA employees through the camera viewpoints while recording instantaneous speeds with the aid of a GPS device. Additional details regarding the Challenge datasets and evaluation criteria can be found at [1].

6. Results

In this section, we analyze the results obtained by applying our tracking and speed estimation models to the Track 1 videos from the 2018 NVIDIA AI City Challenge. We first describe our Challenge result and then analyze potential avenues of improvement for our model.

6.1. Challenge Submission

Our team's best Challenge submission, which had a DR score of 1.0 and an $RMSE$ score of 12.1094, earned an $S1$ score of 0.6547, 0.0017 below the next higher ranked team. While our model had perfect detection performance, the speed estimation component of our method was not accurate enough to be competitive against the top teams, team48 and team79, which earned $S1$ scores of 1.0 and 0.9162, respectively. Given the score of 1.0, it is clear that team48 also had a detection rate score of 1.0 and at the same time managed the lowest $RMSE$ score among the teams.

6.2. Model Analysis

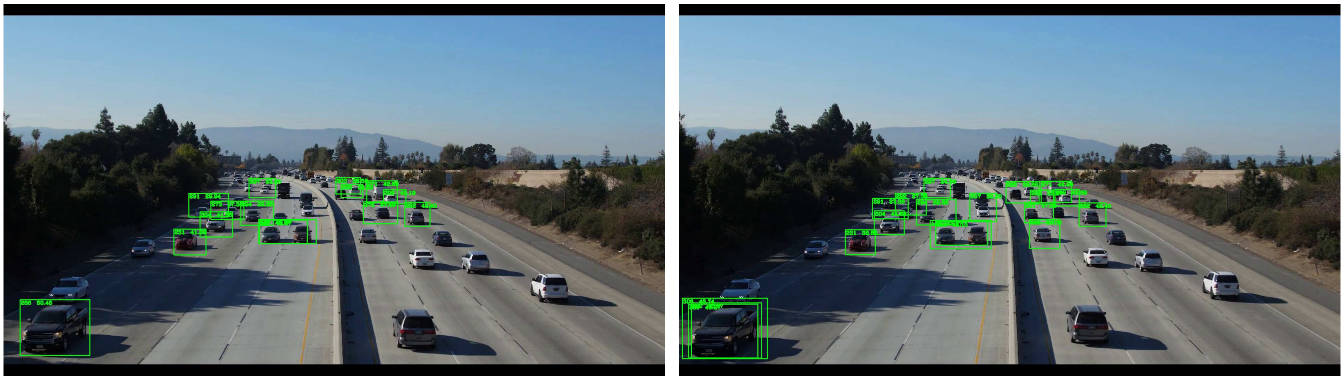
Our best performing model was a constant speed model with maximum speeds of 70, 70, 50, and 30, respectively, for locations 1–4. Our predictive speed models suffered from both lower detection rate and higher $RMSE$ scores than the CS model. Figure 5 shows the predicted speeds for two consecutive frames from Location 1 using the PS (a) and CS (b) models executed with the same parameters. The PS model relies on the optical-flow-based tracklet detection to estimate vehicle speeds and will only output a detection if its speed can be reliably estimated. As such, a number of vehicles that are detected in the CS model are missing from the PS model output.

As a way to better understand the limitations of the PS model, we selected 10 random tracks from each location with a minimum length of 45 and maximum length of 60 frames, which we plot in Figure 7. While some tracks show expected smooth transitions indicative of normal traffic, many display sudden spikes in speed, which seems to indicate the corner feature detector may be choosing alternate similar corners in some frames.

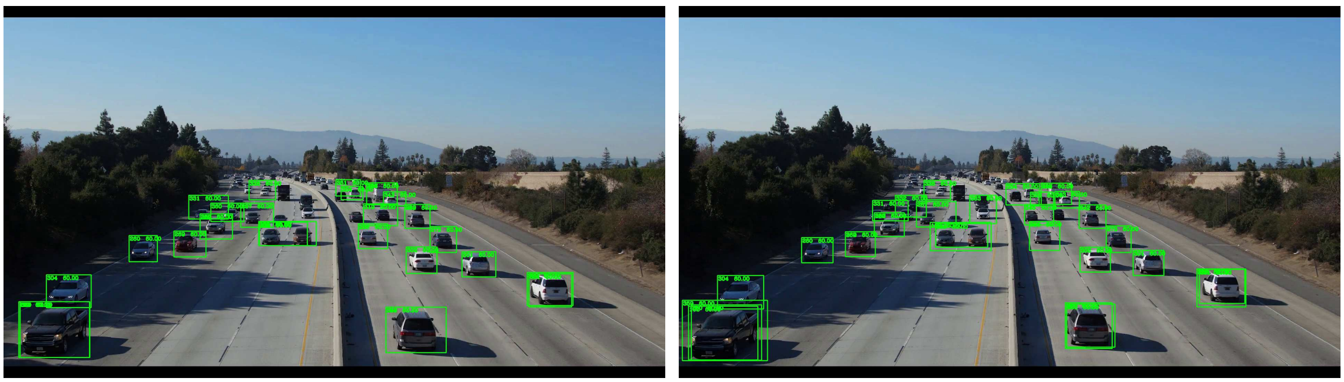
We further verify the variability in speed estimates in the PS model by plotting the distributions of speed ranges (difference between maximum and minimum speed) in tracks of videos in all four locations. Given that most vehicles are only seen for a few seconds while they pass through the frame, they are expected to have almost constant speed and very low variability. Each quadrant of Figure 6 shows, using a line for each video at a given location, a uniform random sample from the speed range distribution in the given video. While some variability is expected due to normal traffic, our model shows excessive variability, with almost 20% of vehicles reporting more than 15 miles/hour variability. The performance is even worse in Location 3, where videos capture quality was impaired by constant camera movement due to wind or bridge vibrations.

7. Conclusion & Future Work

In this paper, we introduced a model for tracking vehicles in traffic videos based on a detect-then-track paradigm, coupled with an optical-flow-based data-driven speed estimation approach, and described our solutions for Track 1 of the 2018 NVIDIA AI City Challenge. Our model performed well but was not as competitive as some of the other Challenge teams, displaying excessive variability. Due to lack of time, we did not compare our method against other detect-then-track algorithms, which we leave as future work. Ad-



(a) Predicted Speed Model



(b) Constant Speed Model

Figure 5. Speed estimates of the predicted (a) and constant (b) speed models. (*Best viewed in color*)

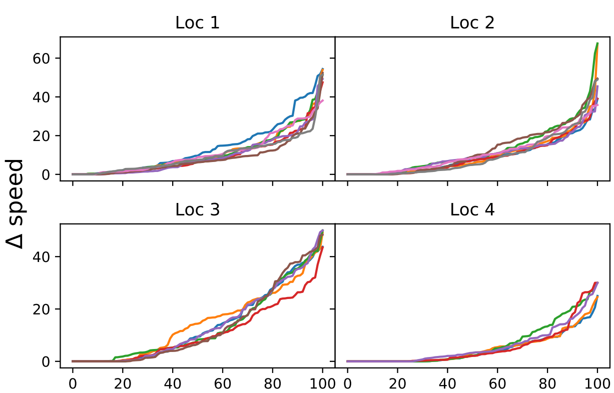


Figure 6. Speed range distribution.

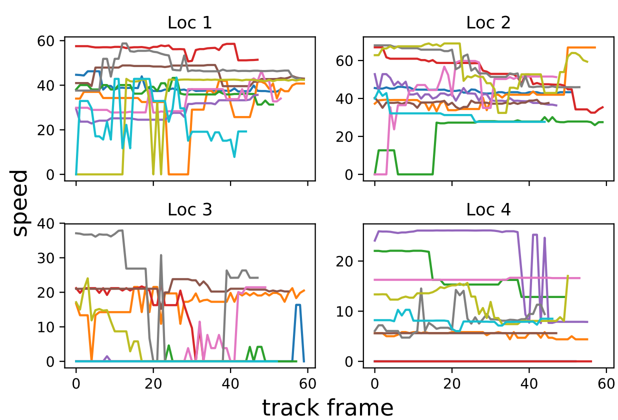


Figure 7. Speed of random tracks.

ditionally, we plan to investigate smoothing techniques for the predicted vehicle speeds which may lead to improved model performance.

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