Article

Show Me a Safer Way: Detecting Anomalous Driving Behavior Using Online Traffic Footage

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Abstract: Real-time traffic monitoring is essential in many novel applications from traffic management to smart navigation systems. The large number of traffic cameras being integrated into urban infrastructure has enabled efficient traffic monitoring as an intervention in reducing traffic accidents and related casualties. In this paper, we focus on the problem of automatic detection of anomalous driving behaviors, e.g., speeding or stopping on a bike lane, using the traffic camera feed that is available online. This can play an important role in personalized route planning applications where, for instance, a user is interested to find the safest paths to get to a destination. We present an integrated system that accurately detects, tracks and classifies vehicles using online traffic camera feed.

Keywords: object detection; vehicle tracking; driving behavior classification

1. Introduction

Traffic management aims at reducing traffic incidents and improving traffic flow. Be it vicious or unintentional, anomalous driving behaviors, as categorised and shown in Figure 1, can directly or indirectly result in traffic incidents and affect transport efficiency [1]. Consequently, knowing where, when and how often these behaviors happen is highly valuable both to the road users, e.g., to adjust their path through safer routes, and the road authorities, e.g., to improve signage. Traditional hardware-based detection techniques, such as inductive loop detector, laser detector and optical detector, are expensive to install and maintain [2]. Moreover, these techniques have limited functionalities when it comes to analyzing the behavior of drivers and other road users. For instance, using an inductive loop detector is not possible to distinguish a cyclist from a car.

Traffic cameras have been widely used to monitor traffic conditions, contributing to urban surveillance [3] and intelligent transportation system [4]. Compared with traditional sensors, widely-installed traffic cameras are more cost-effective and have a wider field of view, thus allowing to monitor multiple lanes [5] and to distinguish between road users. With advances in computing methodologies, in particular in the field of computer vision, as well as the development of more affordable and high-performance cameras, vision-based vehicle detection and tracking is now becoming more feasible, and hence offering great potential [6] for automated traffic information collection and analysis [7].

While research in this area has mainly focused on vehicle detection [8], vehicle tracking [9], and understanding road users' behaviour [10] separately and on an ad-hoc basis, there is a lack of research on integrated systems which combine detection, tracking and driving behavior classification using

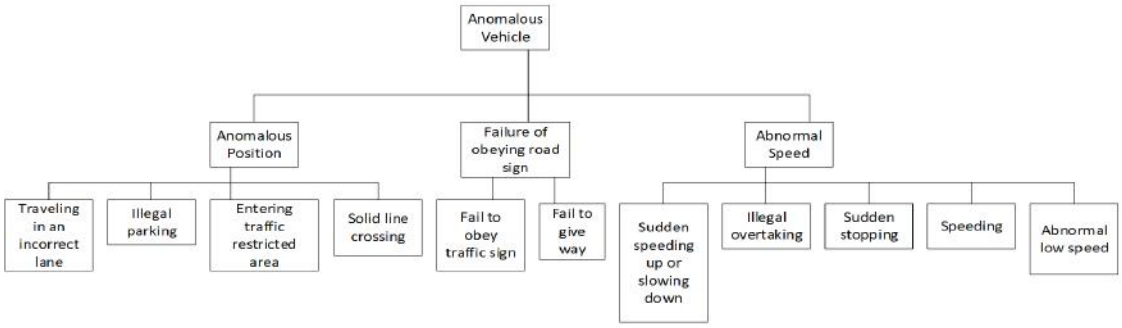

Figure 1. Classification of typical anomalous driving behaviours

traffic footage collected from online traffic cameras. To address this issue, we propose *a web-based integrated system for the detection and analysis of anomalous driving behaviors*, which can be potentially used to provide tailored safe route recommendation for drivers and other road users. Our system can also provide information to traffic management authorities in order to help them make better decisions.

Our system uses traffic footage collected from online sources such as Live Traffic Cameras in Australia [1], and uses the state-of-the-art visual recognition method, Mask R-CNN, which is fast, simple and provides accurate results [11], to first detect the vehicles on the road. The system then tracks the detected vehicles by using the combination of Hungarian algorithm and Kalman filter [9]. The trajectories of the tracked vehicles are analyzed to determine anomalous driving behaviors including speeding, crossing a solid line, and entering traffic restricted areas. The spatio-temporal spread of anomalous driving behaviors is then communicated to the road users in the form of hotspot maps to enable them tailor their routes.

2. Related Work

2.1. Vehicle Detection

Vehicle detection aims at identifying the vehicles and their locations in images. Two main domains of vehicle detection are motion-based approaches [12] detecting vehicles based on their difference with static backgrounds, and appearance-based approaches [8] using prior knowledge to segment the foreground and background using manually designed features such as color [13], texture [14] and Histogram of Gradient (HOG) [15]. By contrast, features extracted by Convolutional Neural Networks (CNN) and other methods based on CNN are automatically learned [16]. Faster Region-based CNN (Faster R-CNN) extracts features on a number of proposal regions, and then performs classification and bounding box regression to detect various objects including vehicles [17]. Combined with Region Proposal Network (RPN) which proposes candidate bounding boxes, Faster R-CNN can perform both hypothesis generation and verification efficiently [18]. As shown in Figure 2, compared with Faster RCNN, Mask R-CNN preserves pixel-level locations to improve the accuracy of the mask, and then adds a branch for predicting segmentation masks on each Region of Interest (ROI), in parallel with a branch for classification and bounding box regression. Mask R-CNN achieves state of the art performance in instance segmentation and object detection, with a fast training and testing speed [11].

[1] https://straya.io/

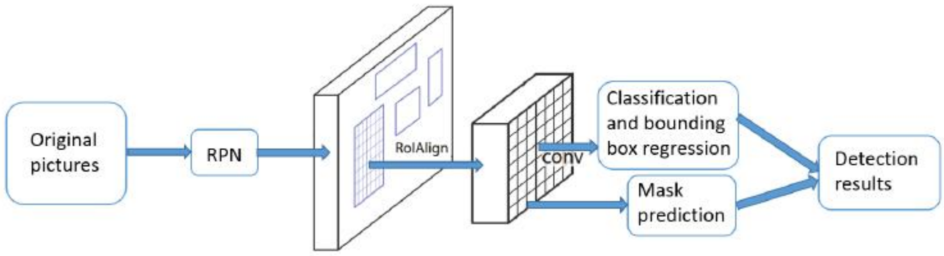

Figure 2. Mask R-CNN framework.

2.2. Vehicle Tracking

Vehicle tracking aims to re-identify the vehicles, derive vehicle trajectories, and predict vehicle positions and motions based on the patterns of previous positions and motions [9]. The methods of video-based tracking can be systematically classified as contour-based method establishing the outline of moving object and updating the outline according to the motion of object [19], feature-based method concentrating on tracking significant features of the vehicle and the distribution of these features [10], and framework-based method in which objects in a framework are assumed to move in accordance with certain distribution patterns like position and velocity [20].

Hungarian algorithm [21] is an optimization algorithm used to solve the assignment problem which deals with the allocation of resources to activities, seeking for minimum cost or maximum profit. The authors in [20] use Kalman filter to predict the centroid of the observed vehicle on successive frames and calculate the measurement errors and prediction errors and update the prediction dynamically. Our system shows that an ensemble method that integrates these two approaches provides a higher accuracy.

2.3. Behavior Classification

Behavior Classification aims at characterizing the behavior of drivers as normal or abnormal, and identifying anomalous events such as sudden stopping and solid line crossing. The authors in [10] classified sudden stopping behavior by setting thresholds for vehicle starting velocity, ending velocity and accelerated speed, and if the corresponding three values of the observed vehicle in the real world are smaller than the set thresholds, the behavior of the observed vehicle can be judged as sudden stopping. For classification of solid line crossing, [10] specifies solid lines as boundary referenced lines and extracts their pixel coordinates, and then computes the variance of the differences between the coordinates of vehicle trajectories and the solid referenced line. If the vehicle keeps moving within a lane, the variance will stay at a correspondingly low level, whereas if the vehicle crosses the solid line to change the lane, there will be a sudden dramatic increase in the variance value.

However, these studies only focused on one or certain specific vehicle behaviors, which limited their compatibility in complex traffic situations. Besides, there is still a lack of an integrated system which combines detection, tracking and classification of anomalous behaviours to detect anomalous driving behaviours based on traffic footage.

3. Methods

To create an integrated system which can be used to detect anomalous driving behaviours based on traffic footage, we perform vehicle detection, tracking and anomalous driving behaviour classification using the steps as explained below.

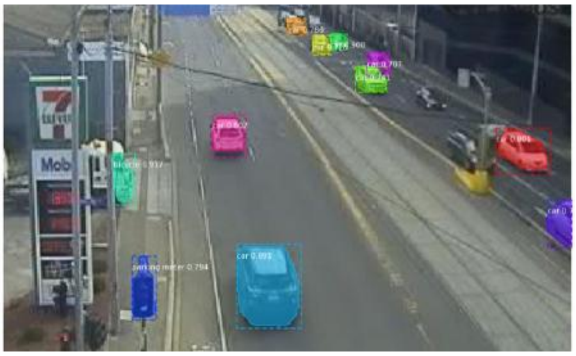

Figure 3. Vehicle detection using Mask R-CNN.

3.1. Vehicle Detection

To detect the vehicles in the frames, we use the Mask R-CNN technique. As shown in Figure 2, Mask R-CNN uses a Region Proposal Network (RPN) to generate candidate object bounding boxes and RoIAlign to extract features and preserve pixel-level locations to improve the accuracy of the mask. The network includes a branch for predicting segmentation masks on each Region of Interest (ROI), in parallel with a branch for classification and bounding box regression. This method is both fast and simple and provides accurate results in instance segmentation and bounding-box object detection [11]. The video footage is converted to a sequence of images, and fed as input to the Mask R-CNN. With pre-trained weights for MS COCO [22] which can detect a wide range of objects (for instance, car, bus, and pedestrian), the resulting class id, frame number, confidence level and the coordinates of the bounding boxes for each detected vehicle are collected and recorded. Vehicle centroids can be calculated as centroids of corresponding bounding boxes. Figure 3 shows an example of vehicle detection in an image frame using Mask R-CNN.

3.2. Vehicle Tracking

Once a vehicle is detected, vehicle tracking aims to determine the centroids belonging to the same vehicle in continuous frames and accordingly derive the trajectories of the vehicles. The Hungarian algorithm assigns the centers of vehicles to the trajectories of those vehicles with the least total cost, which is the sum of distance between centers and trajectories, with the condition that one center is exclusively assigned to one trajectory.

To eliminate the influence of vehicle detection errors on the Hungarian algorithm a Kalman filter is used, which can predict the vehicle centroid location in case it is missed by the detection method. The complete tracking process is shown in Figure 4 and comprises the following steps.

1. Newly appearing vehicles are identified and tracks are created with detected centroids. When the distances between detected centroids and the last centroids in all tracks exceed a predefined threshold, this detected centroid is considered as a newly appearing vehicle.
2. Hungarian algorithm is used to assign the rest of detected centroids to existing tracks by minimizing the sum of cost between assigned detected centroids and predicted centroids in tracks.
3. Kalman filter is used to predict and correct the detected centroids by estimating the centroid of next frame based on given centroid of the current frame.
4. Remove and extract existing trajectories when there is no corresponding vehicle being assigned to these tracks for 5 frames (1 second), which indicates that the vehicle has moved out of the camera range.

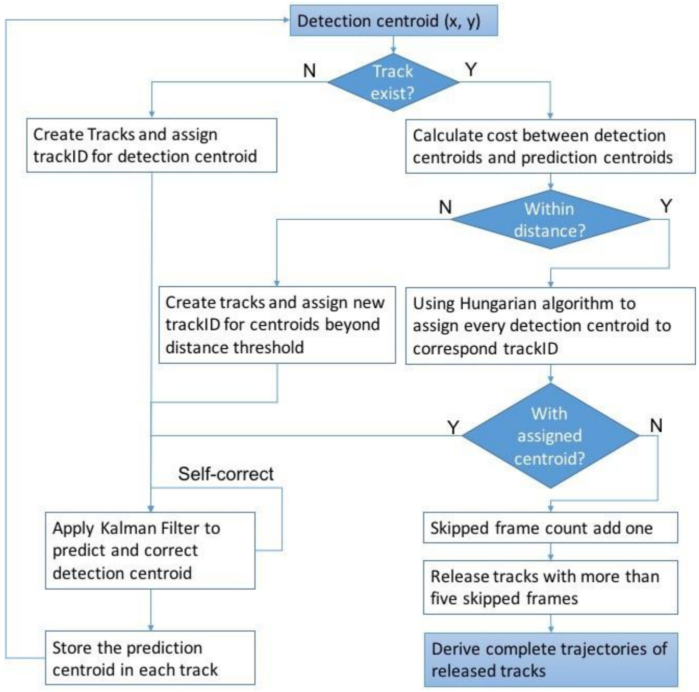

Figure 4. Tracking process.

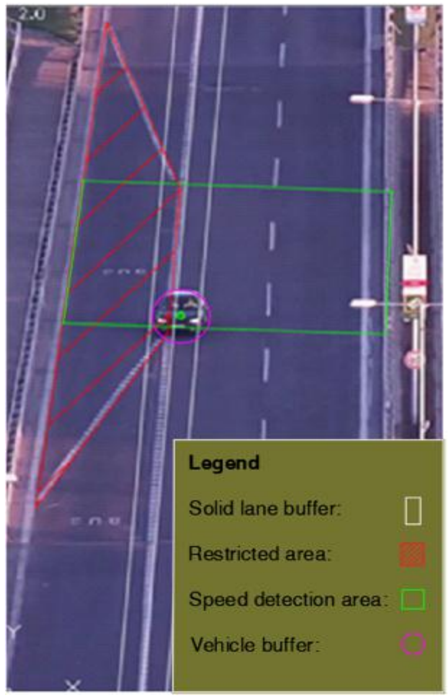

Figure 5. Manually specified regions used for Behavior classification.

3.3. Behavior Classification

The behavior classification aims to determine and classify anomalous driving behaviors and is mainly based on the trajectory information developed in vehicle tracking component. Here we classified three common anomalous driving behaviors:

1. Speeding: Speeding is identified by a comparison between the speed limit and the detected average velocity of the observed vehicle while traveling in a specified region. As shown in Figure 5, two green boundary lines are set for recording where and when a vehicle enters and leaves the region. The positions and frame numbers of a vehicle are recorded once the vehicle passes the upper green line or the lower green line, and the time is recorded correspondingly. To correct the perspective effect of traffic camera, a projective transformation [23] is used to map every point in the footage to its real-world coordinates on the ground plane. For speed calculation the following equation 1 is used:

$$s = \frac{\sqrt{(x_j - x_i)^2 - (y_j - y_i)^2}}{t_j - t_i} \tag{1}$$

   Where s is the speed, (x_i, y_i) and (x_j, y_j) are the centroid coordinates of vehicles on the ground plane, and t_i and t_j are the traveling time between entering the ith frame and leaving the jth frame.

   The variance of the speed of vehicles can be computed by the following equation 2:

$$\sigma_v^2 \approx (\frac{1}{t'}\sigma_x)^2 + (\frac{x'}{t'^2}\sigma_t)^2 \tag{2}$$

   Where σ_x and σ_v are the standard deviation of traveling distance and speed respectively. The initial guessed value of the traveling distance and traveling time are annotated as x' and t'. It is assumed that the distance x and time t are mutually independent. The value of x' should be the distance between the setting boundary lines and the value of t' should be the theoretical required time for vehicles to travel between the green lines.

2. Solid line crossing: Solid line crossing is recognized by establishing whether the trajectory of a detected vehicle intersect with a buffer created around the solid line (two white lanes in Figure 5). If the centroid of the detected vehicle is within the created buffer, it is determined as crossing the solid line.
3. Entering traffic restricted areas: This behavior is identified by the overlapping area between the traffic restricted area shown as the hatched red polygon in Figure 5, and a circular buffer with a predefined radius created around the vehicle centroid. If the overlapping area is larger than a specific percentage of the circular buffer area, i.e., approximately at least half of the car is within the traffic restricted area, the vehicle is determined to have entered the traffic restricted area.

4. Experiments

4.1. Experiment setup

There are two thresholds using in behavior classification:

- For speeding, the uncertainty of the detected speed is σ_v, which corresponds to the confidence interval of 68%.
- For entering traffic restricted areas, If the overlapping area is larger than 50% of the circular buffer area, the vehicle is determined to have entered the traffic restricted area.

To evaluate the performance of our integrated system for detecting solid line crossing and entering traffic restricted areas, the recall, precision and false positives per second are utilized as a measure of the detection accuracy. These three coefficients are defined as:

$$Recall{=}\frac{N_{\mathrm{TP}}}{N_{\mathrm{TP}}{+}N_{\mathrm{FN}}} \tag{3}$$

$$Precision{=}\frac{N_{\mathrm{TP}}}{N_{\mathrm{TP}}{+}N_{\mathrm{FP}}} \tag{4}$$

Where N_{TP} is the number of True-Positives (TP), which is the number of anomalous behaviours that are correctly detected; N_{FN} is the number of False-Negatives (FN), which is the number anomalous behaviours that could not be detected by the system; and N_{FP} is the number of False-Positives (FP), which is the number of anomalous behaviours that do not actually happen but are wrongly detected.

In our system, we used two sets of traffic footage:

- Dataset 1: Our first dataset consists of snapshots of online traffic camera on the intersection Racecourse Rd. and Boundary Rd. (RB) in Melbourne published by Vicroads. Since the snapshot used in this study is refreshed every 120s, our system can only detect certain anomalous behaviors, for example, entering traffic restricted areas. Hence, this dataset was used only for the detection of vehicles driving on the bicycle lane.
- Dataset 2: Considering the low sampling rate of the first dataset, we use recorded traffic footages as the second dataset that are sampled more frequently from 2 highways: Panónska cesta[2] (PA), M7 Clem Jones Tunnel (M7), and the intersection of Huangshan Rd. Tianzhi Rd in Heifei, China[3] (CN). This dataset contained three videos with lengths of 2, 4 and 4 minutes respectively and a total of 3112 frames. Given the higher resolution, we define the anomalous driving behavior as solid line crossing, entering traffic restricted areas and speeding. For the first two categories,

[2] https://www.youtube.com/watch?v=JmFjluIQGJw
[3] http://www.openits.cn/openData2/602.jhtml

we manually annotated the images to establish ground truth for the evaluation of the detected anomalous driving behaviors.

4.2. Results

Several experiments were carried out to evaluate the performance of the proposed system in identifying anomalous driving behaviors. The following sections describe the datasets used in the experiments and the evaluation results for the three anomalous driving behaviors.

4.2.1. Solid line crossing and entering traffic restricted areas

Table 1 shows the detection accuracy for solid line crossing and entering restricted zones in Dataset 2. The relatively low recall for "entering traffic restricted areas detection" may be due to the low resolution of the online traffic cameras. An instance of anomalous driving behavior is shown in Figure 6, where the anomalous behavior (shown as the red rectangle, "CL" means line crossing behavior) is illustrated.

Table 1. Detection accuracy of anomalous behaviors.

Behavior Class	Recall	Precision
solid line crossing detection	0.889	0.865
entering restricted areas detection	0.730	0.964

4.2.2. Speeding behavior

Figure 7 shows the distribution of the estimated speed for the tracked vehicles, which approximately follows a Normal distribution. Therefore, a confidence level can be taken into account dependent on the random error estimation through the calculated speed value uncertainties, which is based on the method of variance propagation, which considers the effect of variables' uncertainties on the uncertainty of a function based on them. Note that the variance propagation can only evaluate random errors associated with the speed estimation. Moreover, because the ground truth of actual speeds is hard to obtain manually, the speed limit of the road was used as the threshold to classify speeding behavior. In our integrated system, anomalous speed, both too high and too low speed, is identified by comparing the speed limit of the road with the estimated speed within a high confidence interval, e.g. 99% corresponding to $3\sigma_v$.

5. Discussion

5.1. The combination of Hungarian algorithm and Kalman filter

When a vehicle is undetected in the successive frame, Hungarian algorithm assigns the center of other detected vehicles into the trajectory of an undetected vehicle, which causes the wrong trajectory shown in white line in Figure 8. The incorrect assignment using only the Hungarian algorithm has a large influence on behavior detection and causes many false positives in results, as shown in Table 2. The table concerns two footage from the Panónska cesta highway, where the on-site speed limit is 60km/h. In this situation, Kalman filter will correct the misassigned center by using a constant velocity motion model to predict the supposed center of the undetected vehicle and use it to replace the misassigned center, thus making the trajectory closer to the real situation, as shown by the colored lines in Figure 8.

5.2. Integration and Visualization

The main feature of the system is its ability to integrate online data collection, vehicle detection, vehicle tracking and behavior classification so that users (urban authorities or road users) can easily obtain the pattern as long as the system has access to a set of traffic footage. The results from anomalous

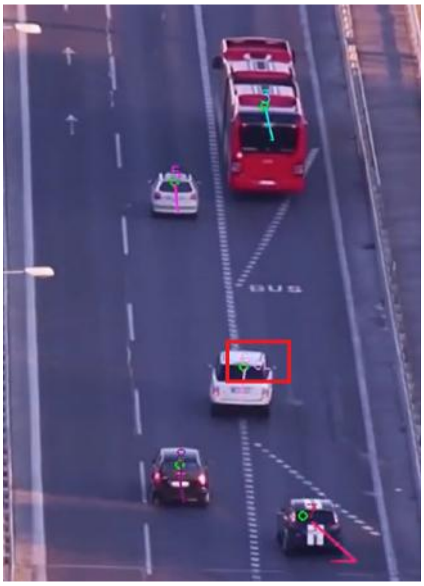

Figure 6. Example of detection result (a solid line crossing behavior).

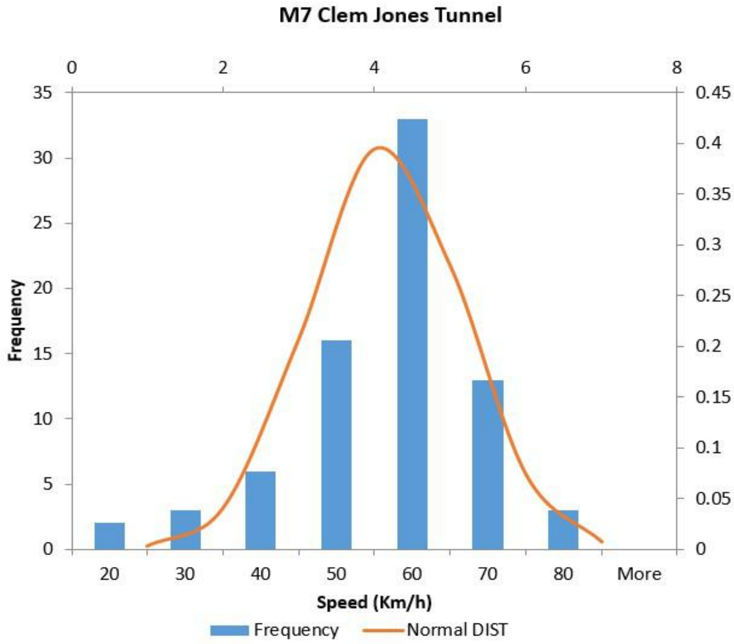

Figure 7. Distribution of speed estimations for M7 in Dataset 2.

Table 2. Detecting speeding behavior with and without Kalman filter.

Indicators	Dataset	With Kalman Filter	Without Kalman Filter
Mean Speed (km/h)	Dataset 1 Dataset 2	56.66 62.46	161.98 57.16
Speed limit within 68% confidence interval (km/h)	Dataset 1 Dataset 2	68.39 64.24	85.07 63.23
Number of speeding behaviors	Dataset 1 Dataset 2	3 10	8 25

driving behavior detection component are then paired with locations of the footage. Information of anomalous driving behavior at certain location and time periods can then be analyzed to generate the respective patterns. For example, for our first dataset (VicRoads), the bicycle lane was set as the traffic restricted area, and when any other objects such as vehicles and pedestrians entering this area, it will be recorded as an anomalous behavior. A bicycle lane with smaller number of such behaviors can be recommended as a 'cyclist friendly' route to individuals. Figure 9 shows an example of a hotspot map that can be created based on the observed behaviors.

5.3. High adaptability

This system can be applied to any multi-object tracking scenarios with only centroids provided, and with a Mask R-CNN model covering wide range of classes of objects. Compared to single-object tracking system, this system can deal with complex situations with various objects mixing and remove interference from unnecessary objects. Moreover, the system can also be adapted to other functions, for instance, automatic identification of solid lines and traffic restricted, thus saving the trouble of manually re-setting the geometrical parameters every time for different footages.

5.4. Limitations

Despite the fact that our system provides high accuracy and high adaptability, it has several limitations which are summarized as follows:

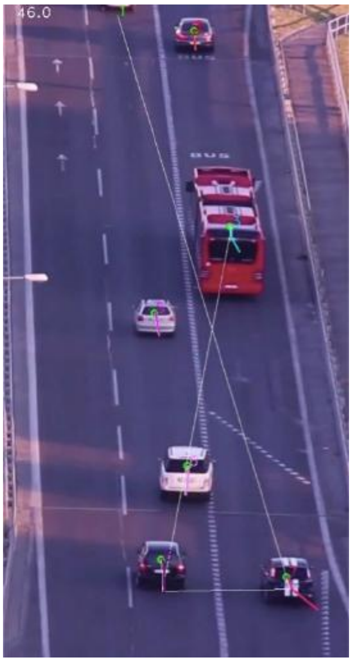

Figure 8. Tracking errors caused by the Hungarian algorithm (white lines) can be corrected by Kalman filter (colored lines).

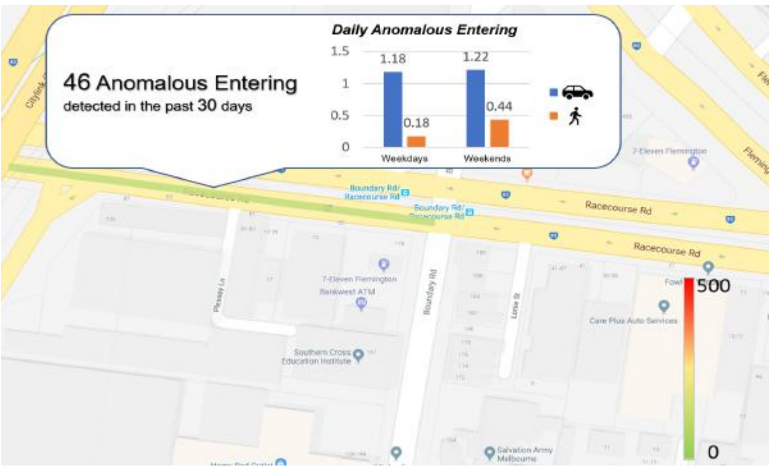

Figure 9. Example of hot spot map showing the number of daily anomalous entering on weekdays and weekends.

Figure 10. One example of footage with low recording angle.

- In scenarios of crowding traffic with a lot of obstacles where the vehicles do not travel smoothly, the Kalman Filter may not be able to correctly predict the movement of the vehicles because the vehicles are overcrowded.
- The impact of recording angle of the camera might cause significant distortions and hence affect the behavior detection. Theoretically, the most appropriate angle for the camera should be a bird's-eye view, thus the potential distortion can be minimized. Conversely, Figure 10 from the intersection of Huangshan Rd. Tianzhi Rd. demonstrates an example of low recording angle, in which the distortion is more severe and the low accuracy appears, as the system simply judges the topological relation between vehicle position and restricted area or solid lane, and for ground truth collection the determination of behaviors are based on the relative position of the vehicle wheels and road marks.
- The accuracy of the system relies heavily on the accuracy of Mask-RCNN detection. As an appearance-based approach, this method depends on prior knowledge, to be more specific, the trained model. Here we used the trained model of MS COCO [22], and therefore the detection cannot perform well when the footages are overly blurred or shot in conditions where the vehicles cannot be identified, for example, night time at roads without streetlights.

6. Conclusions

In this paper, an integrated systems is developed to detect anomalous driving behaviors and visualize the spatial patterns of the distribution of these behaviors using hotspot maps. Overall, the recall and precision rate of the experimental results for solid lane crossing and entering traffic restricted area are around 80%. Regarding the speed detection, variance propagation is used to improve the system fault tolerance due to the a lack of a systematic method to obtain ground truth of vehicle speeds. Hotspot maps, which is developed as an overview of number of detected anomalous behaviors during a certain period, can be used as a tool to detect the spatial patterns of such behaviors. In the future, the accuracy of anomalous behavior detections would be improved though methods including specific training of Mask-RCNN model, optimization of the default setting matrix of Kalman filter, and using other cues of each vehicle as pre-conditions of Hungarian algorithm (for instance, assigned vehicle centroid should have same colour or same type of vehicle centroids in tracks). Automatic detection of solid lines and traffic restricted area can also be achieved, thus saving the trouble of manually re-setting the geometrical parameters every time for different footages. Moreover, the user interfaces, such as hotspot maps would be refined to make it more user-friendly and applicable in a variety of cases.

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