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Cyclist Overtaking Safety Study Using Video Data

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Abstract

While cycling has grown considerably in recent years, it is not as safe as it should be, and the perception of unsafety hinders its further growth. Intersections are the most complex parts of the road network, but cyclists are also particularly vulnerable on road segments when overtaken by motorized vehicles. Laws have been enacted to guarantee safe overtaking events by vehicles with minimum distance and other speed requirements. While there have been several studies on cyclist passing distance using instrumented bikes or vehicles, there have been few attempts at developing an automated system for the safety analysis of cyclist overtaking at a fixed location. This paper presents a computer vision tool to measure the cyclist passing distance and vehicle speeds before, during and after the overtaking. The tool is tested on a case study in Montréal, Canada. It shows that most passing distances are safe, but that most drivers fail to comply with the requirement to decelerate while overtaking cyclists.

Keywords: Cycling Safety; Overtaking; Video Analysis

1. Introduction

The global growth of cycling has been considerable in the recent decade (eco counter, 2019). Cycling is an efficient mode of transportation with little environmental impact that promotes physical activity. It is encouraged around the world by the development of cycling facilities such as segregated bike paths, bike boxes and dedicated traffic lights. Yet, while road safety tends to improve in rich countries, cyclist injuries tend to stagnate and even increase in some places. The actual or perceived risk of injury hinders the growth of cycling despite its promotion and the infrastructure investments.

If intersections may be the most dangerous parts of the road network for all users, cyclists are also vulnerable on road segments when being overtaken by motorized vehicles. Even if safely performed, such maneuvers are uncomfortable for cyclists. That is why jurisdictions are trying to improve cyclist safety through new facilities and new laws. The rules of road have been updated in 2016 in Québec, with a new regulation destined to protect cyclists. When passing cyclists, drivers must 1. reduce their speed; 2. maintain a safe distance between their vehicle and the cyclist

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while passing. Depending on the speed limit, either higher or lower than 50 km/h, the minimum passing distance is respectively 1.5 m and 1.0 m. If one of the conditions is not met, passing the cyclist is forbidden and the driver can be fined.

The law is very precise, but there is no recommendation on how to apply it and verify driver compliance. Sensors can be mounted on a bike for that purpose and have been used in previous studies (Walker, 2007), but few fixed sensors have been tried. On the contrary to a sensor mounted on a bike (or motorized vehicle) that provides continuous temporal coverage of a given cyclist, a fixed sensor provides data for all cyclists in its area of spatial coverage. To the best of the authors' knowledge, there are few tools to measure automatically the passing distance of all cyclists by motorized vehicles at fixed sites. Among available sensors, video sensors have several advantages, in particular their low cost, high resolution and the progress in computer vision methods to analyze them automatically.

The objective of this paper is to develop a computer vision tool for the safety analysis of cyclist overtakings by motorized vehicles by measuring the passing distance and the vehicle speeds, and to validate it in a case study in Montréal, Canada. Drivers compliance with the new Québec rules of the road can be thus evaluated. The paper is organized as follows: past work is reviewed in the next section, followed by a description of the methodology, then by the experimental results, before the conclusion and perspectives for future work.

2. Background

Cyclist safety is most often studied using historical crash data (pia, 2019). For example, Lusk et al. (2011) show the risk of cycling injury is much lower on cycle tracks compared to streets. Because crash data has many shortcomings, which are even more acute for cyclists, proactive methods that do not require to wait for accident to happen have been developed to provide surrogate measures of safety since the late 1960s (Laureshyn et al., 2016). Interest has grown considerably since the mid-2000s and the advent of practical computer vision tools to process video data, extract traffic data (Zangenehpour et al., 2015; Fu et al., 2017) and compute surrogate measures of safety more or less automatically. They have been applied to study cyclist safety at intersections (Kassim et al., 2014), at right-turn channels (Autey et al., 2012) and cycle tracks (Zangenehpour et al., 2016) among others. Other sensors have also been tested, including GNSS sensors from users' smartphones, to detect harsh maneuvers that were shown to be correlated with crashes involving cyclists (Strauss et al., 2017).

Cyclists are particularly vulnerable on roads when they are passed by motorized vehicles. That is why laws have been enacted to regulate the passing distances and driver behaviour in general. Several studies on cyclist overtaking have been done in the past, most of them through the instrumentation of one of the two users, either bikes or motorized vehicles. In one of the most famous study on the topic in the United Kingdom, Walker (2007) and Walker et al. (2014) used an instrumented bicycle with an ultrasonic distance sensor to measure the proximity of passing vehicles. The researchers studied cyclist factors that influence driver overtaking proximity such as helmet use, vehicle type, rider's outfit and rider's gender. They found, among other things, that drivers leave less space when cyclists wore a helmet. Hence, the appearance of cyclists has an effect on driver's behaviour.

Apasnore et al. (2017) measured manually the passing distance between the rider and the vehicle based on video data. In total, 90 hours of data have been collected at six urban streets in Ottawa, Canada, with GoPro cameras. The lateral distances were calculated with the coordinates of the bicycle tire and the car tire compared to the edge line. They found that over 90 % of passing distances were higher than 1,23 m, which exceed the 1 m spacing requirement.

Near 5000 overtaking events have been investigated to study driver-bicyclist interactions using an instrumented vehicle on Michigan's roads in the United-States (Feng et al., 2018). Bezzina and Sayer (2014) used data from an existing naturalistic driving study to examine the lateral positions of vehicles and bicycles based on the right-side line marking. They assumed a bicyclist width of 0,75 m (2,5 feets) and that the cyclist was rolling in the middle of his bike path. After studying multiple road configurations, they found that a maximum of 9 % of drivers pass below three feet of cyclists and 68 % below five feet. The worst road configuration was two lanes in the same direction separated with a dashed line beside a bike path.

Shackel and Parkin (2014) used an instrumented bicycle to examine the proximity and the traffic speed in overtaking events to understand the factors leading to cyclist discomfort. Data was collected from a 31 km path in the City of Liverpool in England chosen to represent multiple road characteristics such as lane width, lane configuration, lane marking and speed limit. First, the mean passing distance between vehicle and cyclist was 1.6 m and 1.7 m respectively for 20 mph and 30 mph roads. Secondly, the most comfortable conditions for cyclists were with the low speed limit, wider roads and no center-line marking.

It appears thus that there have been few attemps to use video data and computer vision algorithms to automatically detect cyclist overtaking events and extract their characteristics, the passing distance and speed of the vehicle.

3. Methodology

The goal of the developed system is to measure the distance between a cyclist and a car while the latter is passing the first, and the speed of the car. While a dedicated method could target these measures specifically, a more generic approach is to detect, track and classify all road users to obtain their trajectories (positions over time) from which the desired measures can be derived. The developed method consists in the following six steps:

1. site selection and video data collection;
2. calibration of the relationship between the road user positions in the camera image and real world coordinates;
3. road user detection and tracking;
4. road user classification as motorized vehicle, cyclist or pedestrian;
5. cyclist passing distance extraction;
6. road user speed extraction.

The first four steps rely on existing tools in the open-source Traffic Intelligence project (Jackson et al., 2013) available on Bitbucket[1]. The camera is installed on top of a telescopic mast tightly attached to a lamp post on the side of the road. The road users are detected and tracked using a feature-based tracking algorithm: feature on moving objects are detected and tracked, then grouped based on motion similarity (Saunier and Sayed, 2006). They are then classified as a motorized vehicle, a cyclist or a pedestrian using several cues, namely their appearance and speed, combined through a support vector machine and majority voting at each instant (Zangenehpour et al., 2015). An example of two well tracked and classified road users is presented in FIGURE 2 (B stands for bicycle and C for car).

The overtaking of a cyclist by a motorized vehicle takes some time, from the instant the vehicle front reaches the rear wheel to the instant the vehicle rear passes the front wheel. The minimum distance between the vehicle and the cyclist can be measured continuously over that time interval, in the case of video data for every image. The difficulty to measure the distance at each instant can be understood from FIGURE 1: all the features tracked on the cyclist and vehicle are projected in world coordinates up to a given frame (the trajectories of each feature, from its detection up to the current instant are plotted) with their respective bounding rectangles aligned with their velocity vectors. One can see the two users seem to overlap, which happens because of projection errors, or more accurately because all feature positions are projected to world coordinates as if they were at the ground level. The homography is a projection from image space to world coordinates at the ground level: if projecting points above the ground, they appear further from the camera than they should be. However, the feature points closest to the camera are rather well projected since they are close to the ground.

The proposed method relies on further projecting these points in curvilinear coordinates along the center line of the road: each point P is projected to its closest point P' on the center line and its curvilinear coordinates are made of the curvilinear distance of the projected point P' to the beginning of the center line (longitudinal coordinate) and the distance from P to P' (lateral coordinate). The closest point of each user to the center line (smallest lateral coordinate), y_v and y_c respectively for the vehicle and cyclist, are tracked during the overtaking. To measure the passing distance, an assumption about the vehicle width w is needed. Using $w = 2.0$ m, the passing distance at each instant is $y_c - y_v - w$. FIGURE 2 illustrates the passing distance measurement over time between the dashed green line for the vehicle's side closest to the cyclist and the full blue line for the cyclist's closest side to the vehicle. The overall passing distance is

[1] https://bitbucket.org/Nicolas/trafficintelligence/

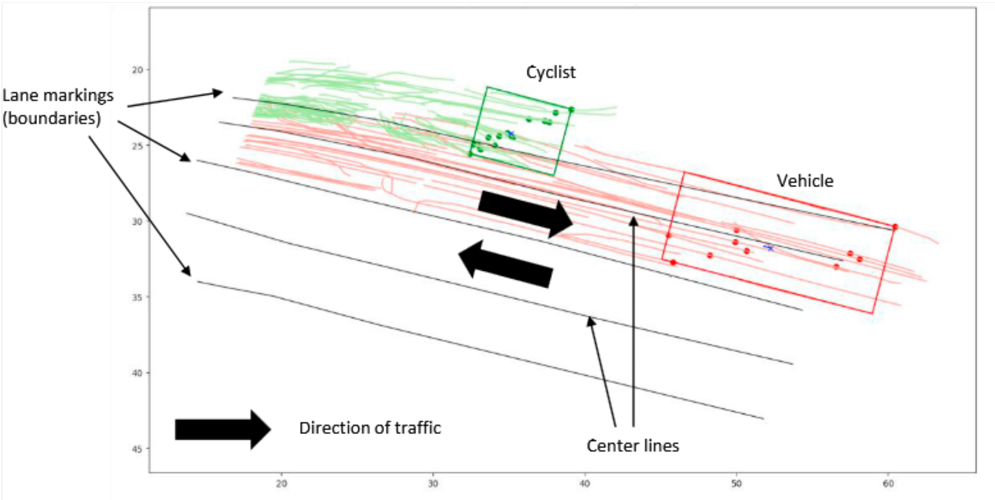

Fig. 1. Example of projected features up to a given instant with the bounding rectangle around each road user (the feature trajectories are the red and green lines with the points for the current position for the vehicle and the cyclist respectively).

chosen as the distance measured at the middle of the overtaking time interval, unless it differs from the next measure (before or after) by more than 30 cm, in which case that measure is taken (the mean is avoided as it would be strongly affected by extreme errors).

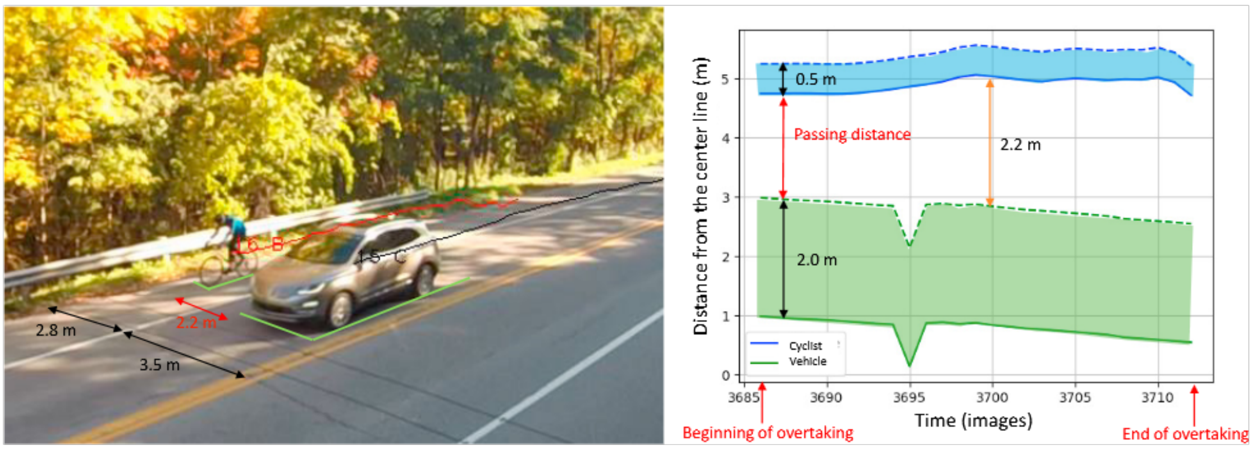

Fig. 2. Illustration of the passing distance as a function of time (the video frame on the left is at instant 3699).

The vehicle speed is also extracted for each overtaking. Each road user speed is computed at the tracking stage as the mean of the road user feature displacements (distance travelled in world coordinates between two successive frames) at each instant. For the analyses, the mean vehicle speeds are computed for the three periods: the overtaking time interval, the period before and after the overtaking. Because the cyclist overtaking can happen anywhere in and outside the camera field of view, these periods may not be complete or captured at all. The minimum period duration to compute the mean speed is two frame instants. For some overtakings, there is no vehicle mean speed before or after.

Furthermore, a speed comparison is done with another technology, namely pneumatic tubes, to validate the video-based vehicle speed measurements. The speed is measured from the video as the mean speed over a fixed distance of 6 m around the tubes, 3 m before and 3 m after, based on the times when the vehicle centroid crosses these virtual lines.

4. Experimental Results

4.1. Data Collection

The video data is recorded with a regular GoPro sports camera using resolution 1280x720 pixels and 30 frames per second. The camera intrinsic parameters and distortion coefficients have been estimated in previous studies, and a homography is estimated for the specific site. The chosen site is the rue Camillien-Houde on the Mont-Royal in Montréal (see aerial and camera images in FIGURE 3). Video data was recorded for around seven hours and a half from 9:30am till 5pm on a Sunday in October 2018. This road is very popular for cyclists who want to train on roads a high gradients: the road goes uphill in the west direction. The speed limit is 50 km/h. 5073 road users were counted by the pneumatic tubes during the video data collection period.

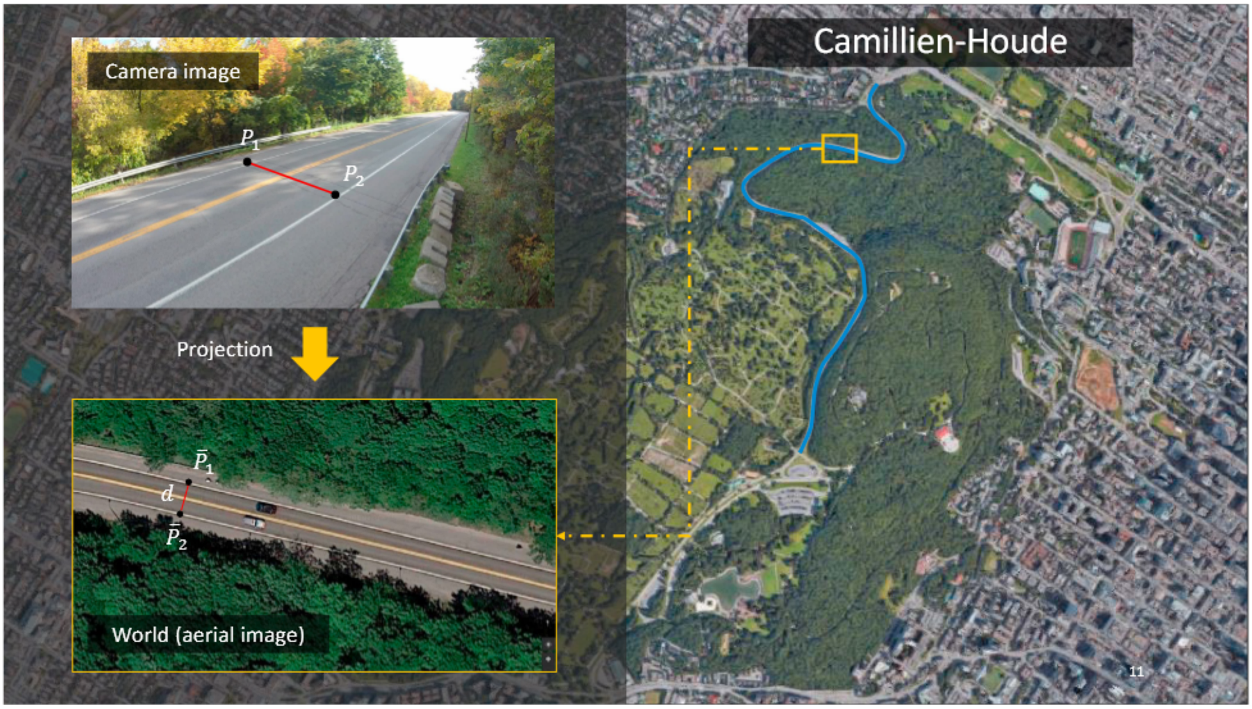

Fig. 3. Site localization with a sample image from the camera.

4.2. Validation

The performance of the tool for the classification of the road users, detecting the cyclist overtakings, measuring the vehicle speed and the passing distance has been evaluated and is reported in this section. Though the speed parameters were adjusted to the users on the site, the classification error was 17.8 % on a sample of 381 road users recorded over one hour. There are two main causes or factors for these errors, large vehicles such as trucks and buses (mainly in the east direction, closest to the camera), and the lighting variations particularly the strong shadows (mainly in the west direction). Large vehicles are often tracked as more than one, and some parts are often misclassified. They also occlude other road users, which may be completely missed or misclassified.

4.2.1. Speed Measures

As stated previously, vehicular speed data was also collected using pneumatic tubes for comparison. While the speeds obtained from the pneumatic tubes are considered the reference or ground truth, that method is not devoid of its own shortcomings. As can be seen in FIGURE 4, some speeds measured by the tubes above 100 km/h are unrealistically high. One can clearly see that most points are under the line of equality (where $y = x$ or all the points would lie if the two sensors agreed perfectly), which means that speeds from video are systematically under-estimated, more so in the west, uphill, direction where speeds are lower.

Errors between the two methods are also computed and presented in TABLE 1. The cases where the speed measured by the pneumatic tubes is higher than 80 km/h are removed from the error calculations. The average relative error in both directions is 13.36 % or 5.43 km/h in absolute terms. In half the cases, the error is below 9.41 %. The error is always larger, in relative and absolute terms, in the east direction. The errors may seem large and may be in part related to errors from the reference sensor but are in line with previous comparison with manually extracted speeds (Anderson-Trocme et al., 2015).

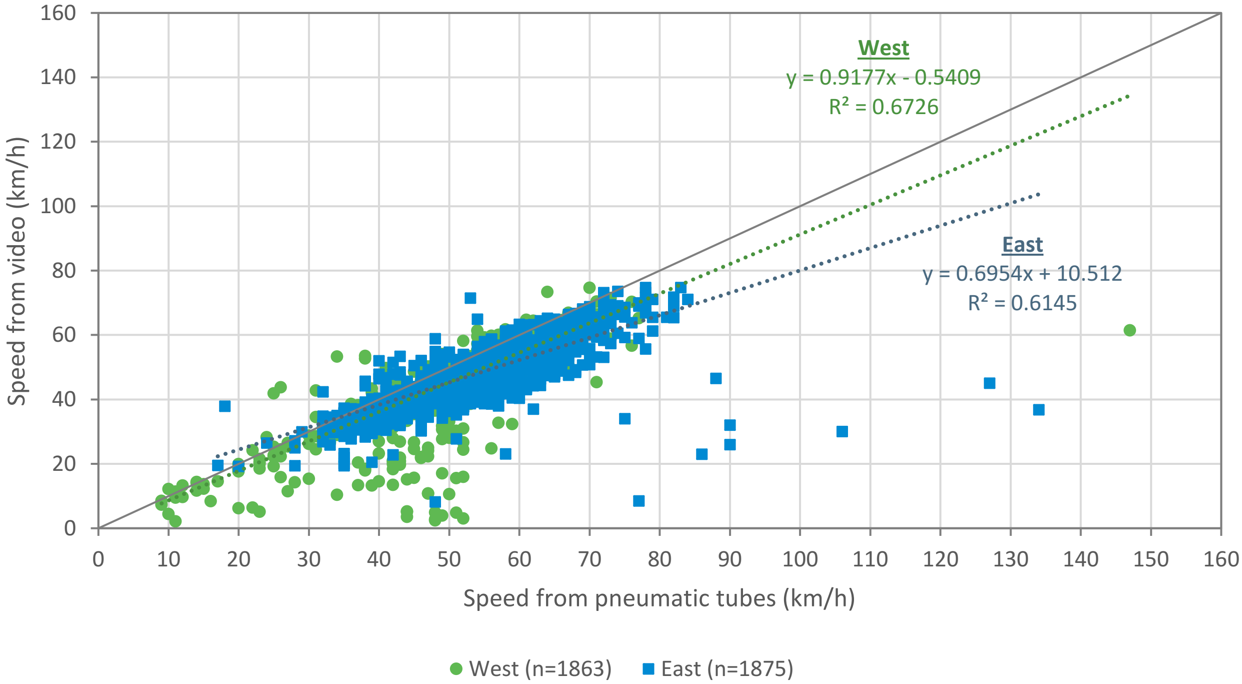

Fig. 4. Scatter plot of the speeds measured by the computer vision tool and pneumatic tubes by direction of traffic.

Error		West (n=1853)	East (n=1861)	Both (n=3714)
Mean	Rel.	13.33 %	13.39 %	13.36 %
	Abs.	(4.79 km/h)	(6.06 km/h)	(5.43 km/h)
Median	Rel.	8.61 %	10.51 %	9.41 %
	Abs.	(3.96 km/h)	(5.19 km/h)	(4.48 km/h)
85^{th} Centile	Rel.	15.00 %	21.68 %	18.31 %
	Abs.	(6.63 km/h)	(9.97 km/h)	(8.49 km/h)

Table 1. Statistics (mean, median and 85^{th} centile) of the absolute error on the speed measurements in absolute and relative terms with respect to the pneumatic tubes.

4.2.2. *Passing Distance Measures*

To validate the passing distance measures by the proposed video-based method, they are measured manually for a subset of overtakings. This is done by clicking on the video on the ground points on the side of the vehicle closest to the cyclist and on the side of the cyclist closest to the vehicle, in both directions. These points are projected to world coordinates to derive the reference passing distance. The accuracy of this manual measure is good since the projection errors are small for ground points.

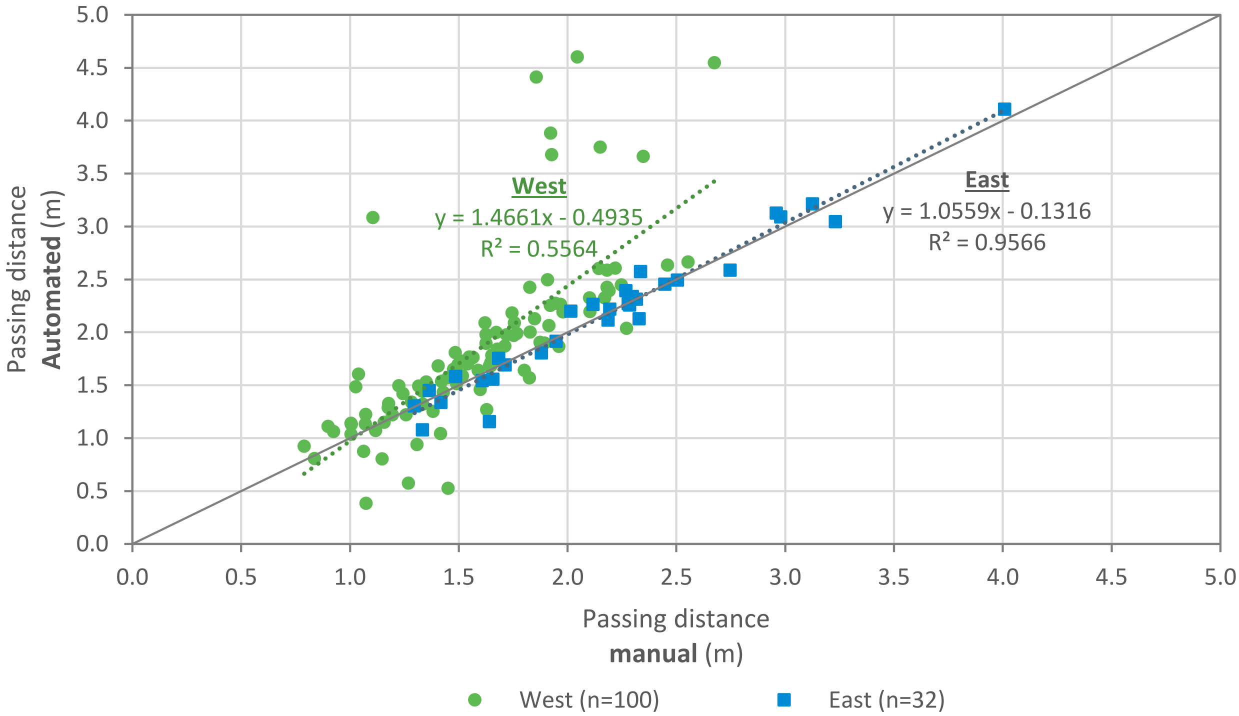

Fig. 5. Scatter plot of the passing distances measured by the computer vision tool and manually by direction of traffic.

As for the speed comparison, the passing distances are presented as a scatter plot in FIGURE 5 and the errors in TABLE 2. The points appear above the line of equality for both directions, meaning that the automated method over-estimates the passing distances. The situation is however quite different for both directions. The performance in the east direction is quite good, as can be seen in the scatter plot or by the reported errors of 5.17 % on average and 4.03 % for half of the measures. This is a different story for the west direction, which corresponds to the measures for the road users that are the furthest from the camera. In that direction, the cyclist, in particular its lowest parts that are crucial for an accurate position, is often partially occluded by the overtaking vehicle. This results in higher errors (21.39 % on average), and particularly a small number of very large errors which influence the average error, as demonstrated by the median that is almost half the average error and the high 85^{th} centile. Overall, the average error is 17.62 % or 29 cm, but half the errors are less than 10 % or 16 cm.

Error		West (n=100)	East (n=32)	Both (n=132)
Mean	Rel.	21.39 %	5.17 %	17.62 %
	Abs.	(0.35 m)	(0.10 m)	(0.29 m)
Median	Rel.	12.67 %	4.03 %	9.51 %
	Abs.	(0.19 m)	(0.08 m)	(0.16 m)
85^{th} Centile	Rel.	30.64 %	8.76 %	26.66 %
	Abs.	(0.46 m)	(0.19 m)	(0.41 m)

Table 2. Statistics (mean, median and 85^{th} centile) of the absolute error on the passing distance measurements in absolute and relative terms.

The performance of the passing distance measurement is also reported in terms of categories or intervals. The first cut-off values were chosen according to the rules of the road, 1.0 and 1.5 m, followed by 2.0 m. The errors can be visualized in the confusion matrix in TABLE 3: the measure or classification errors are counted in the non-diagonal cells. If the method was perfect, all non-zero cells would be on the diagonal (in bold in TABLE 3). The over-estimation by the automated method are clearly visible, but one can see that there is only one error by more than 0.5 m. Overall, 71.2 % of the passing distances are well classified.

		Automated				
		< 1 m	1-1.5 m	1.5-2 m	≥ 2 m	Total
Manual	< 1 m	**2**	2	0	0	4
	1-1.5 m	6	**26**	11	1	44
	1.5-2 m	0	3	**30**	15	48
	≥ 2 m	0	0	0	**36**	36
	Total	8	31	41	52	132

Table 3. Confusion matrix of the passing distance classes predicted by the computer vision tool and compared to the manual measure.

4.2.3. *Cyclist Overtakings*

In addition to the 132 overtakings for which the automated and manual passing distances were compared, the computer vision tool detected another 23 overtakings that were not evaluated in terms of passing distance because the cyclist position was not visible for a manual measure. There were also 84 false alarms made by the tool, or 35 % of all automatically detected overtakings. These are mostly caused by the previously discussed large vehicles tracked as several road users and classification errors, in particular other types of road users classified as cyclists. Finally, the tool also misses road users and therefore overtakings: among 256 manually detected overtakings, the automated tool missed 39 % of them. The main reasons for the misses are the occlusions by the vehicles and tracking errors when two distinct road users are tracked as one.

4.3. *Case Study*

The distribution of the passing distances measured by the tool are presented in TABLE 4. One can see that for both directions, 6 % of overtakings are dangerous given the 50 km/h speed limit and that all these dangerous overtakings happen in the west direction (uphill). Overall, overtakings happening in traffic in the west direction are much more dangerous than in the east direction: in the west direction, 34 % of overtakings occur with less than 1.5 m distance, which may be also considered dangerous given the actual vehicle speeds, a significant proportion of which is above 50 km/h (see FIGURE 4).

Passing Distance	West (n=100)	East (n=32)	Both (n=132)
< 1.0 m	8.0 %	0.0 %	6.0 %
1.0-1.5 m	26.0 %	15.6 %	23.5 %
1.5-2.0 m	34.0 %	21.9 %	31.1 %
≥2.0 m	32.0 %	62.5 %	39.4 %

Table 4. Proportion of observations by passing distance class by direction of traffic.

The advantage of the presented computer vision tool is the tracking of road users and the ability to obtain data characterizing the whole overtaking, before and after. This allows to validate whether drivers comply with the rule to reduce their speed during the overtaking. TABLE 5 presents the means speeds for three periods, before, during and after the overtaking (denoted respectively $\bar{s}_b$, $\bar{s}_d$ and $\bar{s}_a$) and their statistical comparisons. The mean speed differences are also displayed as boxplots in FIGURE 6. Before overtaking, the vehicle speeds are on average 45.75 km/h and 50.83 km/h respectively in directions west and east. In the west direction, it increases significantly by 3.59 km/h, while in the east direction it decreases by a non-significant 3.49 km/h. After the overtaking, the mean speeds decrease significantly in both direction. This shows that most drivers do not comply with the new rules of the road. This result is confirmed by the analysis of the speed differences by vehicle (during-before and after-during), as displayed in FIGURE 6, which are statistically different from 0. This lack of compliance may be explained by the drivers trying to minimize the duration of the overtaking in the west direction, while in the east direction, drivers may be focused on controlling their downhill speed. It may also be related to the very large shoulders (2.5 m wide) on the sides of the road. When looking at all the vehicle speeds, with and without a cyclist overtaking, using a regression of the speed as a function of the longitudinal coordinate, it appears that the mean speeds are larger in cyclist overtakings.

Period	West (uphill)	East (downhill)	Both
Mean speeds ± standard deviations			
Before (km/h)	45.75 ± 7.50	50.83 ± 12.89	46.95 ± 9.27
During (km/h)	49.35 ± 8.65	47.34 ± 11.73	48.86 ± 9.48
After (km/h)	45.52 ± 10.12	41.69 ± 10.78	44.56 ± 10.38
Statistical test for the means (*: significant at 95 % confidence)			
$\bar{s}_d - \bar{s}_b$ (km/h)	**+3.60 ***	-3.49	+1.91
$\bar{s}_a - \bar{s}_d$ (km/h)	**-3.83 ***	**-5.65 ***	**-4.30 ***

Table 5. Mean speeds and standard deviations before, during and after the overtaking and statistical comparisons

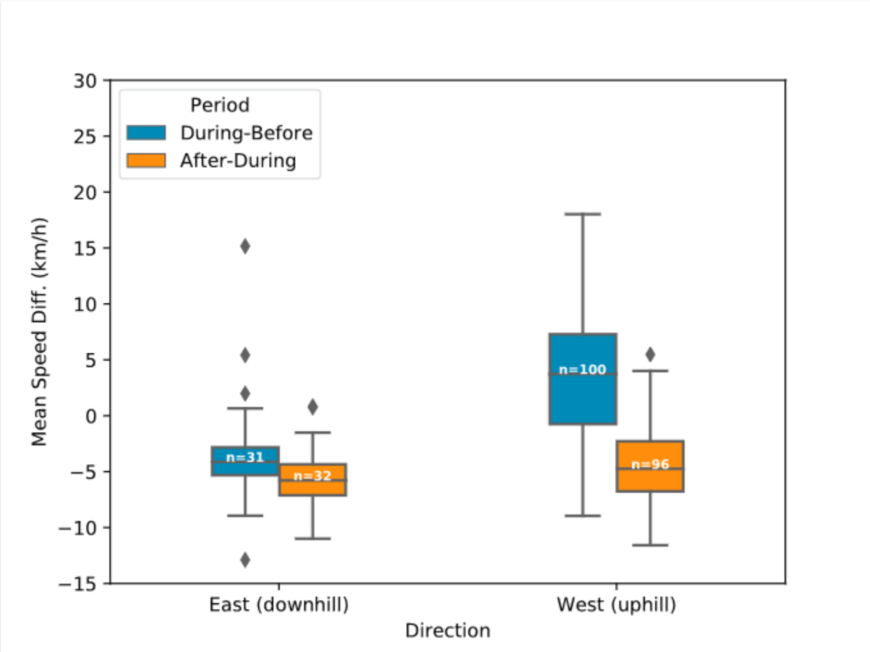

Fig. 6. Mean speed differences between the periods by direction of traffic.

5. Conclusion

This paper has presented a new computer vision tool to study the safety of cyclist overtakings by motorized vehicles. The tool is validated on a case study in Montréal, Canada, and shows promising results. The performance in terms of classification, overtaking detection, vehicle speed and passing distance measurement is reported. It appears that most drivers respect the minimum passing distance for roads with 50 km/h. However, most do not comply with the required deceleration during the overtaking. The drivers seem focused on managing their speed in the downhill direction and minimizing the duration of the overtaking, at the expense of the cyclist safety in case of an accident.

The presented method has several limitations. Computer vision is a very active field of artificial intelligence in constant progress. New tracking and classification methods can be added to the tool to improve its performance. Other methods to compute the vehicle speeds and the passing distances can be developed and compared. For example, better boundary detection of vehicles would help (Sochor et al., 2018). Other measures of cyclist safety, in particular used in surrogate measures of safety like time-to-collision can be estimated for the cyclist-vehicle interactions before and during the overtaking. The case study should be expanded to different days of the week and several sites to test how the site characteristics may be associated with the driver overtaking behaviour. Road user attributes like gender and the wearing of a helmet can also be semi-automatically extracted to better understand the factors associated with cyclist safety in these situations.

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