Characterizing the Cyclists' Path - Overtaking Maneuver Detection and Vehicles' Speed Estimation

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***Abstract*— The traffic pollution is a scourge of urban areas and several transportation policies have been adopted to increase the use of sustainable transportation, such as bicycles. To develop this desirable trend and design new infrastructures, policy makers require tools for cyclists' risk assessment. In this paper, a video-based method to estimate overtaking maneuvers and vehicles' speed is proposed. It was possible to geo-reference these stressful events for riders, providing a framework for path characterization concerning roads' suitability and safety for cyclists.**

The proposed method is based on license plate recognition and tracking of approaching vehicles near cyclists surroundings. A new data set with realistic bicycle scenarios in urban roads, gathered with an action camera located at bicycle's handlebar together with smartphone's GPS data, is made available and used as case of study. Allowing to compare distinct streets and urban areas based on the speed of detected overtaking maneuvers. The results achieved are very promising concerning path's characterization for cyclists.

***Index Terms*— Cyclist, Overtaking Maneuver, License plate recognition, Vehicle Speed**

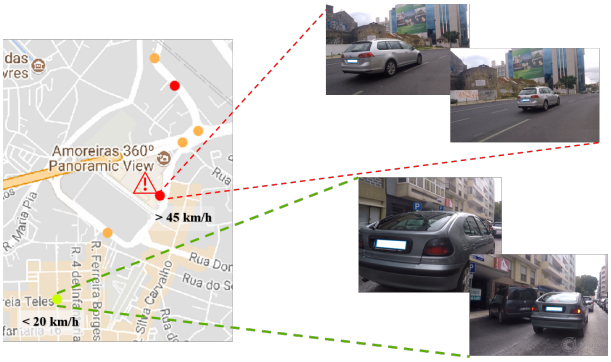

Fig. 1: Occurrences mapping based on GPS data and speed estimation for overtaking maneuvers performed near cyclists. In this image two distinct scenarios are represented, a car performing an overtaking maneuver over 40 km/h and below 20 km/h, highlighted with red and green marks in the map, respectively.

I. Introduction

In the last few years the number of cyclists in urban environments has increased. This trend can be seen on recent reports from Department for Transport [8] from the United Kingdom, which have revealed that in 2014 more than 20,000 cyclists were injured in the reported road accidents.

This unfortunate fact has given rise to the develop of systems aimed at improving bicycle users' safety.

Based on the mentioned report and the analyses performed by The Royal Society for the Prevention of Accidents (RoSPA) [22] it is possible to identify that most accidents take place in urban areas.

It is also possible to pinpoint the most common cycling accidents, which is important information when studying the city's roads for danger assessment. The most common accidents are presented as follows:

- Motor vehicle merging into cyclist's path;
- Motor vehicle turning across cyclist's path;
- Cyclist riding into the path of a motor vehicle;
- Both vehicles moving straight ahead;
- Cyclist turning right from both a major road and a minor road;

Several methods have been proposed to classify roads suitability regarding bicycles circulation, in [3] and [27], and lane width, vehicles speed and traffic flow are the most used parameters as well as events with vehicles are among the most risky situations [10]. As they are onmipresent indicators, the number of overtaking maneuvers and speed limit as very important to evaluate cyclist path's safety.

On the same path of our previous work [6], [26], we aim to assist cyclists on travel path decision by mapping the street safety based on previous collected and georeferenced videos. Based on image processing, Vieira *et al.* [26] proposed an automatic classification of cyclists' maneuvers, like turn right and left, or interactions between cyclists and vehicles. This previous work also shown the correlation between these interactions and stressful events. In [6], we proposed a new descriptor to access the route risk from the cyclist perspective, taking into account the type of obstacles (people, cars, etc.) on the route.

The main goal of the presented work is the estimation

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of vehicle proximity and speed in order to identify dangerous maneuvers performed in cyclist's surroundings. A new approach to estimate vehicle proximity and speed is proposed based on license plate detection and tracking from data provided by a camera located at the bicycle's handlebar.

Accurately identify overtaking maneuvers occurrences and estimate the corresponding vehicle speed in each specific track section is very important to correctly characterize streets. Therefore, these two modules will be the main focus of the present work.

With data gathered from specific streets it will be possible to build a data set based on up to date bicycle data. A data set composed by images sequences and GPS data from cyclists trips can be found at: *http://users.isr.ist.utl.pt/∼mncosta/projects/smartbike/*.

This development, together with previous works of [6] and [26], aims to provide a more reliable risk assessment system for street characterization aimed at bicycle circulation. Also in these works, a smartphone application was developed and used to gather data from a smartphone device, which allowed to collect data from each cyclist's ride for later direct upload to a database.

This paper is organized as follows: in the next section, related work is presented; vehicle detection and tracking approaches are described in Section III; experimental results are evaluated in Section IV; finally, conclusions and future work are draw in Section V.

II. Related Work

Driving systems using smartphones or other sensors as a platform which focus on bicycle's traveling environment have been developed in the last years. In [25], drivers are warned by sound if a vehicle approaches from behind, through a camera installed in the rear, performing a risk assessment based on proximity.

An application prototype is proposed in [11], relying on bicycle-to-vehicle automatic communication to exchange safety relevant information and to alert both users to the presence of potential threats. With GPS data on position, speed and heading obtained through drivers' and cyclists' devices is possible to estimate the time-to-stop (TTS).

Other option is to diverge from accident prevention and instead focus on accident responsiveness. Such is the case of notification systems, tasked to immediately contact the emergency service in case an accident happens. An example of this is eCall [21], a crash notification service for portable and nomadic devices, among others.

In our previous developments, in [6] and [26], event detection (overtaking, turning, stopping etc.), was performed based on the orientation of optical flow vectors in order to estimate direction and orientation of the surrounding objects [26]. Besides this, a new approach on how to identify maneuvers based on image processing techniques was presented concerning bicycles' environment.

With the same goal a proximity perception of the surrounding objects has been developed in [6]. This, together with the knowledge of cyclist trajectory based on the estimation of the focus of expansion, is used in order to predict potential collisions.

Outside of bicycle specific studies, several approaches have been developed to analyze driving behavior. An important portion of them use multiple sensor systems to gather data, as in [15].

Others noteworthy studies follow different strategies, such as: detect risky driving patterns [13]; introduce a driver training system to prevent road accidents due to unsafe driving [19]; and provide driver assistance systems [17].

A. Vehicle Detection and Tracking

In recent years, several studies in the areas of Autonomous Driving have been developed, with special focus on vehicles detection, maneuvers evaluation and tracking. Playing a special role for traffic surveillance systems, they provide useful information for traffic flow control and evaluation.

Concerning vehicle detection and tracking, the use of a non-static camera represents a real challenge to estimate its pose and speed.

To address the need of improving autonomous driving systems, several benchmarks have been developed, such as KITTI [14] which focus on object scene flow, estimating 3D motion fields, using two high resolution stereo systems, a laser scanner, and a localization system.

B. Vehicle Speed Estimation

In the field of Autonomous Driving, vehicle speed estimation represents a topic of research and study. In order to detect and predict possibly dangerous it is fundamental to estimate position and speed of any object appearing in the car's field of view.

Traffic surveillance systems have been developed in order to estimate vehicles' speed, using stationary cameras, in [18], [24] and [4]. These are based on motion vehicle detection techniques, supplemented with lane and object detection techniques.

More recently, in [16] vehicle speed estimation is performed with an average error of 1.12 m/s by resorting to deep learning architectures for depth and motion estimation.

In contrast to traffic surveillance systems that are under a fixed camera pose restriction, the developed approach's observer is located on a moving platform, which increases the problem's complexity due to the lack of information such as camera pose, ego-motion and foreground-background segmentation.

C. License Plate Recognition

Concerning traffic surveillance and security control systems, license plate recognition represents an important tool, making possible to identify traffic violations, tracking cars for urban surveillance systems, automatic detection, among others.

Due to environment variations, such as non-uniform illumination conditions (weather, luminosity variation during the day, etc.), vehicle motion, viewpoint changes and complex backgrounds scenes, license plate recognition has proven to be a complex challenge without a one size fits all solution.

Typically, license plate recognition involves two main stages: 1) license plate region detection and 2) license number recognition.

Since 1990, this topic has been a matter of study, from simple approaches using color based methods, in [5] and [4], or edge based methods, as in [12] and [20], to more complex ones involving machine learning techniques, such as Convolutional Neural Networks, in [2].

In order to find a compromise between computational cost and result quality, some approaches combine more than one feature and different methods simultaneously. Such it the case of [28], in which a combination between Haar-like features and edge-based methods is proposed.

Regarding android applications, an automatic license plate recognition using a mobile device has been proposed in [9], based on OCR methods (Tesseract engine and Neural Networks).

Recently, an open source Automatic License Plate Recognition library, OpenALPR [1], has been released and will be used in the detection module of this work.

III. Proposed Approach

The developed work is a vision-based vehicle detection and tracking system. It focuses on vehicle's license plate, processing real-world data gathered with an action camera located at the bicycle handlebar.

All acquired data is uploaded through the android app to the servers to be processed offline. During processing, each license plate vehicle is detected and tracked.

One of the main challenges of this problem has to do with the quality of the analysis data. This handicap is due both to the simplicity of available hardware (a non-static camera) and poor image stabilization, due to the trepidation, consequence of bicycles natural movement. This is a characteristic of bicycle trips not easily solvable, resulting in less stable and more noisy footage than of a vehicle's dash cam, for example.

The system has 4 main modules: 1) Vehicles Detection, 2) Vehicle Tracking, 3) speed estimation, and finally 4) Maneuvers classification. In Fig. 2 the implementation process is presented.

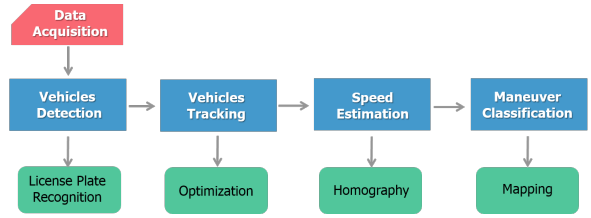


Fig. 2: Implementation process from a vehicle's detection to maneuver identification.

Each module works independently from each other, i.e. the approach performed in the first stage for vehicle detection with license plate recognition could be replaced for any other detection strategy, as long as the outputs maintain the same structure.

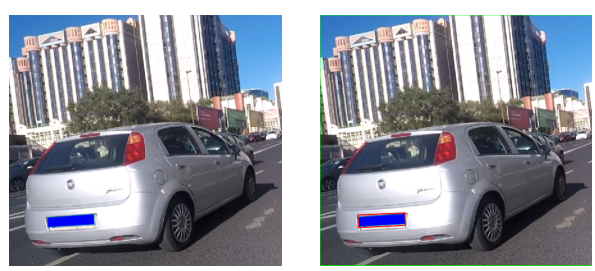
A. Detection

Object detection method will be based on license plate recognition, using OpenALpr software, as mentioned before, which will provide both license plate corners coordinates in image sequences and license plate character sequence.

A priori information of license plate dimensions, in this case a Portuguese license plate, will be the key issue to compute transformation matrices between the reference frame (camera) and detected license plates.

1) License Plate Recognition: As we mentioned before, we localize the vehicles in a video by recognizing its licence plate in each frame. This recognition process is performed by OpenAlpr software. This module applies a set of pre-defined homography transformations to each frame in order to remap the plate region to a new orientation without rotation or skew. Since we aim to detect a specific maneuver, and the possible orientations and positions between vehicles and cyclists are known, we can easily set those transformations.

The input data corresponds to an image as illustrated in Fig.3 .



(a) (b)

Fig. 3: License Plate Recognition. (a) Input image; (b) Output image.

By imputing a frame of real-life footage, Fig. 3(a), OpenALpr outputs a license character combination and

corresponding set of corner coordinates, Fig.3(b). These outputs will be used in the tracking module.

This software is able to locate several license plates in a single image, and for each detection identify a subset of possible character combinations with corresponding confidence levels.

B. Tracking

Based on licenses plate features and their location in the images it is possible to track vehicles in consecutive frames. The correspondence between detected plates in the present frame t and previous ones is computed solving the following linear program:

$$x^* = \text{argmin}_x \quad c^T x \tag{1}$$
$$\text{s. t.} \quad Ax \leq b \tag{2}$$
$$A_{eq}x = b_{eq} \tag{3}$$
$$x \geq 0 \tag{4}$$

where x is the stacked vector of matrix X, and represents the optimization variable, and where c is the stacked vector of matrix C. Considering m vehicles in frame $F-1$ and n detections in frame F, matrix C is given by

$$C = \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1m} \\ c_{21} & c_{22} & \cdots & c_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ c_{n1} & c_{n2} & \cdots & c_{nm} \\ c_{n+1,1} & c_{n+1,2} & \cdots & c_{n+1,m} \end{bmatrix} \tag{5}$$

Each element c_{nm} represents the final cost of associating a new detection n with the previous vehicle m.For instance, if x_{nm} is equal to the value one than the cost, c_{nm}, of associating a new detection, n, with a previous vehicle, m, will be selected. Since matrices A (2) and A_{eq} (3) are totally unimodular, the solution of this convex optimization problem is integer [23].

In order to improve method robustness concerning possible errors of license plate detection (e.g. characters and location misleading), the last detections of a vehicle m occurred at frames F, $F-1$ and $F-2$ were considered as the following expression shows,

$$c_{nm} = wb_1 c_{nm_F} + wb_2 c_{nm_{F-1}} + wb_3 c_{nm_{F-2}} \tag{6}$$

The cost of associating a new element n to a specific detection of a vehicle m in a certain frame i is given by c_{nm_F}, which depends on the number of similar letters, distance between license's centroids in consecutive frames and lapsed time.

$$c_{nm_F} = l_{nm_i} - w_1 \log(\frac{\delta_d}{d_{nm_F}}) - w_2 \log(\frac{\delta_r}{r_n - r_v}) \tag{7}$$

The term l_{nm_F} quantifies how many similar letters a new license plate n and a tracked license plate m_F have in common.

Since character recognition output results for the same license plates varies in different instance, there was the need to add more variables, taking into account the difference between centroids and time intervals.

The term d_{nm_F} expresses the difference between centroids of licenses m_F and a new detection n. Here, logarithm function is used in order to penalize the part of the cost function associated with l_{nm_F} values. For values above the defined threshold δ_d, the cost value increases. Otherwise, when the distance between the centroids is small, the cost function decreases, which contributes for a possible matching.

A time contribution part has to be taken into account, once an overtaking maneuver is performed at short instances of time. Time intervals above a certain threshold δ_t penalize the final cost value c_{nm_i}. The variables r_n and r_v, represent current time instance and the last time vehicle m was detected, respectively.

The influence of time and distance between licenses centroids is determined by a set of $weights = [w_1, w_2]$, which were tuned empirically.

Finally, the set that includes all active tracked vehicles is given by $\mathcal{V} = \{v_1, v_2, ..., v_m\}$, which includes for each vehicle a subset of m_F detections of the same vehicle.

If there is no possible correspondence between a new detection n and tracked vehicles in $\mathcal{V}$, a new vehicle is added to $\mathcal{V}$ and in the next iteration a new column will be added to the cost matrix. In order to deal with new detections without correspondences, we add an extra row to C in Equation (5) where each entry - $c_{n+1,1}, \cdots, c_{n+1,m}$ - has the same value γ.

In this stage, all tracked vehicles $\mathcal{V}$ are obtained by solving the optimization problem (1-4) for each frame.

C. Vehicle Speed Estimation

In order to estimate the transformation and rotation of a planar object in two images it is necessary to compute and decompose the homography matrix, which allows to map an object in the first image into the second image and vice-versa.

The camera displacement can be extracted through an homography decomposition process. The relationship between two corresponding points q (q^x, q^y) and q' (u,v) can be described as:

$$\lambda \begin{bmatrix} q^x \\ q^y \\ 1 \end{bmatrix} = H \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} \tag{8}$$

where λ represents a scale factor and H is a 3 x 3 homography matrix. Solving equation (8), it is possible

to obtain a set of equations that can be represented in a matrix form,

$$A_i h = 0 \tag{9}$$

where A_i is a 2 x 9 matrix, and h is a vector with 9 elements with the entries of matrix H.

Each point correspondence provides two independent equations. Since H has 8 degrees of freedom, given a set of four corresponding points, it is possible to find a solution. From this set of points we can define a set of equations Ah = 0, in which A is formed by the elements of each matrix A_i, for each corresponding points, and h is the vector of unknown entries of matrix H. Final A matrix will have dimension 8×9 and a 1-dimensional null-space that corresponds to the solution space for h.

1) Pose Estimation: Considering P_i as the reference plate coordinates in the 3D world and p_i the points on the image of the reference frame, it is possible to write the following map

$$\begin{bmatrix} u_i' \\ v_i' \\ \lambda_i \end{bmatrix} = K \begin{bmatrix} R & t \end{bmatrix} \cdot \begin{bmatrix} p_i^x \\ p_i^y \\ p_i^z \\ 1 \end{bmatrix}, i \in \{1, 2, 3, 4\} \tag{10}$$

where K is the intrinsic camera matrix, R a rotation matrix, t a translation vector and α a scalar factor. Regarding to the reference plate, $p^i = \begin{bmatrix} p_i^x & p_i^y & p_i^z \end{bmatrix}$ is the 3D location of corner i.

Since the camera observes a planar object, it is possible to consider the reference plate at the plane $p^z = 0$ and estimate the homography matrix, presented as follows.

$$\lambda_i \begin{bmatrix} u_i \\ v_i \\ 1 \end{bmatrix} = \underbrace{K \begin{bmatrix} R' & t \end{bmatrix}}_{\text{H}} \cdot \begin{bmatrix} p_i^x \\ p_i^y \\ 1 \end{bmatrix} \tag{11}$$

where the pair (u_i, v_i) is the 2D projection of corner i and R' contains the two first columns of R.

With à prior knowledge of license plate dimensions, p_i^x and p_i^y are known, together with the detection of license's 4 corners in the image and intrinsic camera matrix K is possible to estimate rotation matrices $\mathcal{R}_0^m = \{R_1^m, R_2^m, ..., R_F^m\}$ and translation vectors $t_0 = \{t_1^m, t_{2)}^m, ..., t_F^m\}$ for the tracked vehicle m in F frames.

These transformations map the 3D reference plate's points to the corresponding 2D coordinates in each frame, according to (10 and 11).

Since it is possible to compute H and the intrinsic camera matrix K is known, R' matrix and translation vector t are estimated according to

$$\underbrace{K^{-1}H}_{\text{G}} = \alpha \begin{bmatrix} R' & t \end{bmatrix} \tag{12}$$

Given matrix G' composed by the first two columns of G, R' is the closest orthogonal matrix closest to G' as the following optimization problem states

$$R' = \text{argmin}_X \quad ||G' - X||_F^2 \tag{13}$$

$$\text{s. t.} \quad X^T X = \text{I} \tag{14}$$

Although this problem is non-convex due to the constraint, it has a closed-form solution. Computing the singular value decomposition (SVD) of G',

$$G' = U \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} V^*, \tag{15}$$

R' is given by

$$R' = UV^*, \tag{16}$$

Estimating R', the translation vector t and the scalar factor α are computed according to the following expressions

$$\alpha = \frac{\lambda_1 + \lambda_2}{2}, \tag{17}$$

$$t = \frac{G''}{\alpha} \tag{18}$$

where G'' is the last column of G.

The translation vector between license plates in two different frames can be computed as $t_{(i,j)}^m = t_j^m - t_i^m$. With F frames, we have the set of translation vectors between all license plates in F frames, $t_{(1,2)}^m, ..., t_{(1,F)}^m, ..., t_{(F-1,F)}^m$.

In this case, we can compute the speed for each translation vector, based on the translation values $t_{(i,j)}^m$ and corresponding time intervals.
A new set $sp^m = \{sp_{(1,2)}^m, ..., sp_{(1,F)}^m, ..., sp_{(F-1,F)}^m\}$ is defined, where $sp_{(i,j)}^m = \frac{||t_{(i,j)}^m||}{(r_j - r_i)}$.

D. Maneuver Identification

This being said, it is possible to distinguish if the camera is approaching or moving away, which is equal to determine if the vehicles (license plates) are moving away or approaching respectively and consequently determine if the cyclist is being overtaken by a vehicle or if it is performing an overtaking maneuver to a vehicle.

For simplicity reasons, in the example presented the camera moves only along z-axis (no variation along x-axis and y-axis), and as a consequence $\Delta dist_{(n,n+1)}^m = \Delta z_{(n,n+1)}^m$, where $dist_{(n,n+1)}^m$ represents $||t_{(i,j)}^m||$.

In Fig. 4, distance measurement between two consecutive detections of the same vehicle is represented. l_n and l_{n+1} represent two license plates detected at different instances of time. If $z_{n+1} > z_n$ camera is moving away, therefore a vehicle is performing an overtaking maneuver. Otherwise, $z_{n+1} < z_n$ and the

camera approaches a vehicle, performing an overtaking maneuver.

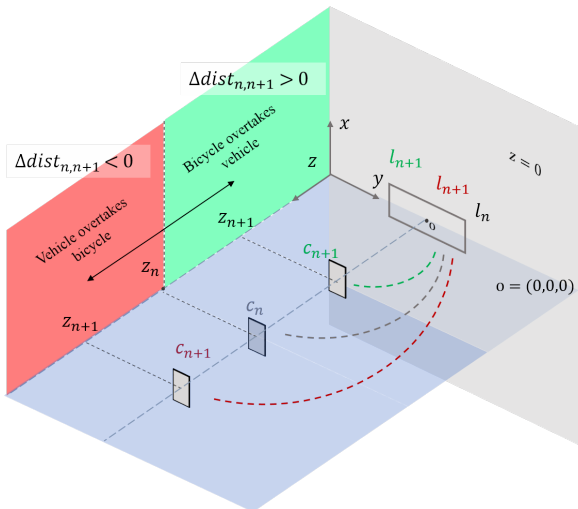


Fig. 4: Distance measurement between two detections, l_n and l_{n+1} represent two license plates detected at different instances of time. Vehicle performing an overtaking maneuver, $z_{n+1} > z_n$; Cyclist performing an overtaking maneuver, $z_{n+1} < z_n$.

E. Mapping

Detection and tracking results together with GPS data gathered with a smartphone, allow to identify where the overtaking maneuvers occurred, and characterize specific streets and neighborhoods.

For each trip, an occurrences map has been created.A color range was defined in order to represent certain speed intervals, as shown in Fig. 5.

Fig. 5: Representation of overtaking maneuvers detected for a single trip.

IV. Results

A. Overtaking Maneuver identification

More than 7 hours of bicycle trips were processed, with almost 120 kilometers traveled at different times of the day. Parameter γ that allows to identify new detections without possible correspondences, was set to 350. The weighted parameters were set with the following values $(w_1, w_2, w_{b1}, w_{b2}, w_{b3})$ = (100,10,0.5,0.35,0.15).

Results analysis allowed to conclude that detection's performance decreases with distance. Therefore, 3 types of overtaking maneuvers were considered in order to perform a detailed evaluation based on lane delimitation.

Besides this, identifying overtaking maneuvers speed performed near cyclists is extremely important in order to assess risk and safety conditions.

Each type of overtaking maneuver is illustrated in Fig.6. Results for each type of maneuver are presented in Table I.

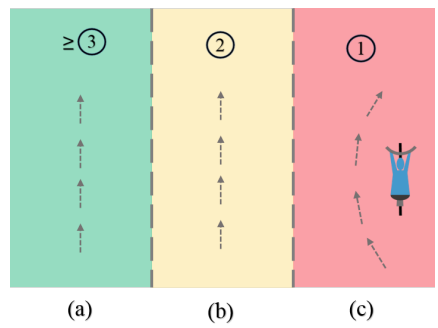


Fig. 6: Overtaking zones based on lane division. (a) Overtaking type 3; (b) Overtaking type 2; (c) Overtaking type 1.

A scheme of predefined zones is presented above, which aims to represent several possible scenarios, in which the tests have been performed. From neighborhoods with roads with only one lane to more complex ones (increased traffic flow, number of lanes, parking areas, among others).

Determine detection's performance for overtaking maneuvers of type 1 and estimate vehicles' speed error will be the main focus of this evaluation. Each time a vehicle overtakes a cyclist sharing the same lane it is considered as an overtaking of type 1.

Overtaking maneuvers performed for more than three lanes apart from the cyclist were considered as type 3, in Fig. 6(a) , and will not be considered for results analysis.

TABLE I: Detection results for each type of overtaking maneuver.

Overtaking Maneuver	Detected	(%)	Total
Type 1	187	78.9	237
Type 2	143	47.9	298

A total of 187 overtaking maneuvers of type 1 over

237 were correctly identified. The results for overtaking detection are presented above in Table I.

False positives (FP) correspond to misleading results due to incorrect detection or tracking of vehicles, and correspond to 5.71 % of the total number of identified maneuvers.

All overtaking maneuvers of type 1 that failed to be identified have been considered as false negatives (FN), 21.1%.

Poor lightning conditions and poor image quality due to the natural trepidation caused by bicycle movement, makes this detection a real challenge once license plate identification depends heavily on lightning condition and image stabilization. Speed estimation is based on the coordinates of detected license plates, which if not correctly estimated could lead to incorrect speed estimation measurements.

Analyzing the results presented in Table I is possible to take the following conclusions concerning overtaking of type 1:

- **78.9%** of overtaking maneuvers were correctly identified.
- **5.71%** of detections performed are false positives.

Regarding, overtaking maneuvers of type 2, only 47.9% were identified, which emphasizes how overtaking maneuver detection performance decreases with distance.

B. Speed Estimation Error

As far as the authors are aware, there is no available data set with ground truth values concerning vehicle's speed estimation moving at bicycles surrounding, and with image sequences taken on a bicycle.

This being said, in order to compute speed estimation error, 95 overtaking maneuvers were analyzed. The real license plate coordinates were determined by hand and the correspondent speed values computed. Final results were determined for two distinct events: 1) vehicle overtakes bicycle and, 2) bicycle overtakes vehicle, with 4.5 km/h and 6.34 km/h of error, respectively.

The difference between the error of being overtaken and be the one that overtakes, is due to the fact that mostly of the overtaken vehicles associated with a large error correspond to parked cars. In this cases, the cars emerge at the right side of the road and a small number of detections is performed for each vehicle. Few detections to a vehicle hinder outliers identification performed in the tracking module.

The parameters defined in vehicle detection module, were chosen to identify licenses for overtaking maneuvers performed at bicycle's left side, in detriment to the right side. Therefore an increased error for vehicles merging at bicycles' right side is expected.

C. Application

The traveled areas were segmented into 7 zones, as shown in Fig.7. For each area a subset of roads were selected to perform a detailed comparison and possible conclusions. A brief description of each area is presented as follows.

- Area A: represents a small neighborhood (Campo de Ourique) with roads with only one lane and parking areas.
- Area B: roads with more than 2 lanes, where the average speed and traffic flow increase.
- Areas C: roads with one to two lanes, cycle lanes and mixed traffic zones (speed limit above 30 km/h).
- Area D: roads with one to three lanes and large roundabouts.
- Area E: roads with one to two lanes, cycle lanes and large roundabouts.
- Area F: main avenue that connects to the historical center.
- Area G: historical center, requested area that is under restricted circulation laws, due to the overload vehicles circulation. Cycle lane areas.

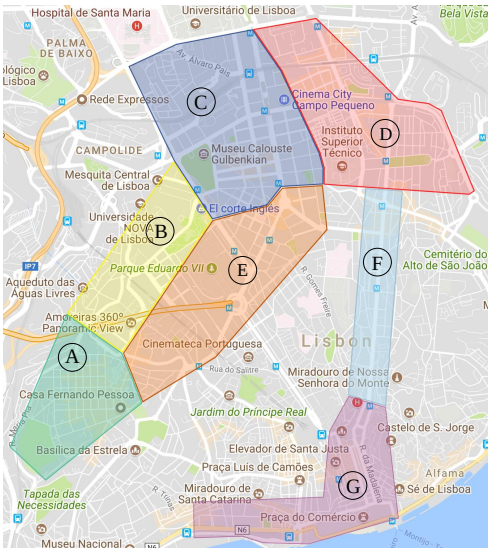


Fig. 7: Representation of traveled areas segmented into 7 different zones.

A total of 288 overtaking maneuvers have been identified in these areas, final results are presented in Table II.Based on the results obtained it was possible to draw the following conclusions.

More than 70% of overtaking maneuvers that occurred inside neighborhoods (area A) are performed below 30 km/h. This values are highlighted in Table II.

In the other hand, areas with roads with increased number of lanes and traffic flow, as in area B present

TABLE II: Overtaking maneuvers detections results with area and speed range specification.

Speed \ Area	A	B	C	D	E	F	G	Total
sp $\leq$ 20	59.09%	12.20%	50%	22.41 %	27.78%	24.36 %	66.67%	84
20 $<$ sp $\leq$ 30	18.18%	21.95%	18.75%	15.52%	47.22%	15.38%	19.05%	61
30 $<$ sp $\leq$ 40	13.64%	43.90%	18.75%	25.86%	19.44 %	24.36%	9.52%	69
sp $>$ 40	9.09%	21.95%	12.50%	36.21%	5.56%	35.90%	4.76%	66
Total	22	41	32	58	36	78	21	288

more than 60% of overtaking maneuvers performed above 30 km/h.

In area D, results seem to be distributed in all ranges, this suggests that this area could be divided into different sections in order to obtain more conclusive results. In area E, 75% of overtaking maneuvers were detected at less than 30 km/h.

Similar to area A, area G is by far the area where overtaking maneuvers were performed with the lowest speed, 85.71% of overtaking maneuvers were performed under 30km/h, fact that could be explained by the existence of several cycle lanes on this area.

Finally, area F represents a main street, that connects to the historical center of the city, and as a consequence is the street with less video samples and more overtaking maneuvers detection (28%) over the total number of overtaking maneuver detections for the entire data set, which emphasizes how requested this street is compared with others. In this street, 60% of the overtaking maneuvers where performed above 30 km/h.

D. Streets Characterization

For each area, a set of main roads were chosen for evaluation purposes. These roads are possible candidates to suffer changes in order to increase the network of bike lanes [7].

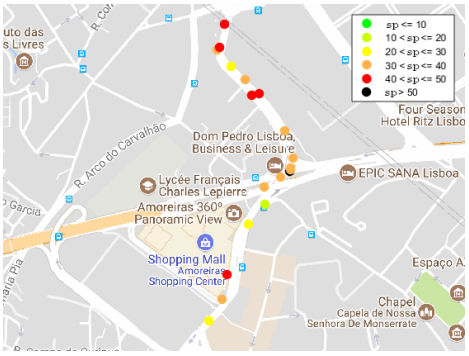
1) Avenida Conselheiro Fernando de Sousa and Rua Carlos Alberto da Mota Pinto: In this area represented in Fig. 8(a) the traffic flow increases (14%) comparatively to area A (7.6%), once the streets covered in this area, present completely different characteristics.

Avenida Conselheiro Fernando de Sousa highlighted in Fig.8(a) has 3 lanes for each direction, parking areas on the right side of the road and ends at a complex intersection. The results reflect these characteristics with 93% of overtaking maneuvers performed above 30 km/h.

After the intersection Rua Carlos Alberto da Mota Pinto emerges with only 2 lanes, connected with Avenida Conselheiro Fernano de Sousa through a complex intersection.

The number of detected overtaking maneuvers has remain the same for the two streets, however a difference between the values for speed is noticed. In Rua Carlos Alberto da Mota Pinto 43% of overtaking maneuvers were detected below 30 km/h, in contrast to Avenida Conselheiro Fernano de Sousa, in which 40% of the overtaking maneuvers were detected above 40 km/h.

(a)



(b)

Fig. 8: Representation of all overtaking maneuvers detected in several trips in 2 specific streets. (a) Avenida Conselheiro Fernando de Sousa and Rua Carlos Alberto da Mota Pinto highlighted; (b) Georeference results.

V. Conclusions and Future Work

A new method for velocity estimation is proposed in this work, based on license plate detection and tracking,

in order to identify and classify overtaking maneuvers performed by vehicles in bicycles' surroundings.

A method to estimate overtaking maneuvers speed has been presented, together with an occurrences map creation, providing a framework for later path characterization concerning bicycles' suitability and safety.

Tracking approach is based on an optimization problem that takes into account the number of similar letters, distance between corners' coordinates and time interval between several licenses plate detections.

Overtaking maneuvers speed estimation together with an occurrences map creation, provide a framework for later path characterization concerning bicycles' suitability and safety.

Furthermore, the proposed approach is suitable for implementation in real time systems, through an adaptation of detection module that requires an off line process for the presented approach. The results achieved can be used to complement existing approaches to assess risk of approaching vehicles as in [25] and alert the drivers, contribute to path characterization, as in ([26] and [6]), and provide useful information for classifying roads concerning bicycle suitability accordingly to the criteria mentioned in [3] and [27].

It was possible to differentiate different urban areas based on the velocity of detected overtaking maneuvers. Besides this, the results obtained matched the expected results, based on static classification of specific urban areas, concerning traffic flow and speed limits.

Characterize calm neighborhoods (area A and G) where at least 60% of detected overtaking maneuvers were performed under 20 km/h, to more requested areas, where almost 60% of overtaking maneuvers were detected with speed values above 30 km/h.

The developed method works with independent modules, which represents an advantage since different strategies can be considered to each module in order to improve results.

In this problem context, Portuguese's license plate were being identified as generic European license plate. Character recognition module could be adapt to identify sequences of symbols with a known structure, or other approaches could be applied, focus on specific features to more complex methods.

License Plate recognition performance depends heavily on lightning conditions and poor image quality, caused by the natural trepidation caused by bicycle movement. An improved mechanism to hold the camera could be considered in order to acquire more data and achieve more robust results, once speed estimation is based on the coordinates of detected license plates, which if not correctly estimated could lead to incorrect speed estimation measurements.

The proposed approach can be improved by defining new sets of parameters to handle more specific events, such as bicycle overtaking moving cars, which represent an important information to characterize roads concerning traffic flow.

It would also be worthwhile to identify parking areas, which may influence the bicycle suitability of a road.

Besides the detailed approach, collecting more data in different areas at different hours of the day using cyclists with different experience would provide a more complete data set.

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