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Automatic vehicle trajectory extraction by aerial remote sensing

Carlos Lima Azevedo[a,]*, João L. Cardoso[a], Moshe Ben-Akiva[b], João P. Costeira[c], Manuel Marques[c]

[a] LNEC, National Laboratory of Civil Engineering, Lisbon, Portugal
[b] MIT, Massachusetts Institute of Technology, Cambridge, USA
[c] IST, Instituto Superior Técnico, Lisbon, Portugal

Abstract

Research in road users' behaviour typically depends on detailed observational data availability, particularly if the interest is in driving behaviour modelling. Among this type of data, vehicle trajectories are an important source of information for traffic flow theory, driving behaviour modelling, innovation in traffic management and safety and environmental studies. Recent developments in sensing technologies and image processing algorithms reduced the resources (time and costs) required for detailed traffic data collection, promoting the feasibility of site-based and vehicle-based naturalistic driving observation.
For testing the core models of a traffic microsimulation application for safety assessment, vehicle trajectories were collected by remote sensing on a typical Portuguese suburban motorway. Multiple short flights over a stretch of an urban motorway allowed for the collection of several partial vehicle trajectories. In this paper the technical details of each step of the methodology used is presented: image collection, image processing, vehicle identification and vehicle tracking.
To collect the images, a high-resolution camera was mounted on an aircraft's gyroscopic platform. The camera was connected to a DGPS for extraction of the camera position and allowed the collection of high resolution images at a low frame rate of 2s. After generic image orthorrectification using the flight details and the terrain model, computer vision techniques were used for fine rectification: the scale-invariant feature transform algorithm was used for detection and description of image features, and the random sample consensus algorithm for feature matching. Vehicle detection was carried out by median-based background subtraction. After the computation of the detected foreground and the shadow detection using a spectral ratio technique, region segmentation was used to identify candidates for vehicle positions. Finally, vehicles were tracked using a k-shortest disjoints paths algorithm. This approach allows for the optimization of an entire set of trajectories against all possible position candidates using motion-based optimization.
Besides the importance of a new trajectory dataset that allows the development of new behavioural models and the validation of existing ones, this paper also describes the application of state-of-the-art algorithms and methods that significantly minimize the resources needed for such data collection.

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Keywords: vehicle trajectories extraction; driver behaviour; remote sensing.

* Corresponding author. Tel.:+351-21-8443541; fax: +351-21-8443552.
E-mail address: cmazevedo@lnec.pt

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1. Introduction

The study of detailed driving behaviour heavily depends on data availability, as traffic micro-simulation models try to capture sub-second vehicle interactions and drivers' decisions. In the last couple of decades safety and driving behaviour modelling research has devoted efforts to the collection and analysis of such detailed traffic data through vehicle-based, site-based or mixed methods.

Vehicle-based methods make use of probe vehicles equipped with multiple sensors that travel in the traffic stream and collect time series information on the behaviour of a test driver and/or adjacent vehicles (Neale et al., 2005). However, these studies provide limited vehicle trajectory data, including trajectories of a small number of instrumented vehicles and snapshot trajectories of adjacent vehicles. Site-based methods make use of sensoring technologies installed in delimited areas for detailed road traffic trajectories collection. Recent advanced sensor technologies, such as RADAR (Aoude et al, 2011) and infra-red (Bhattacharya et al, 2011) may also be found in the literature, but photo and video cameras have been the main tools used in site-based trajectories extraction (Hoogendoorn et al., 2003, Hranac et al, 2004, Laurenshyn, 2010). The developed methods can be classified depending on the type of observation, either static or dynamic. Sensors may be placed either on poles, cables and high-rise buildings (static) or on airborne vehicles such helicopters, aircrafts drones and satellites (dynamic).

Although the main video-based trajectory extractions are based on static sensoring, airplanes and helicopters have already been used as platforms for dynamic observation and trajectory extraction in driving behaviour research. Despite the apparent (space and time) limitations of all these data sets, they allowed for several important developments on traffic flow theory,driving behaviour analysis and transportation systems impacts modelling (Ossen et al, 2008, Toledo et al, 2009, Knoop et al 2009, Jie et al 2013).

Previous methods struggled with adverse weather effects, image stabilization and orthorrectification, the vehicle tracking efficiency, budget limitations and a considerable manual work burden. In this paper we present a new method for automatic vehicle trajectory extraction from a sequence of aerial images that minimizes all these effects. Gyro stabilizing equipment, terrain modelling and advanced computer vision techniques helped to enhance the image referencing process, while colour algorithms brought several advantages to the shadow and vehicle detection processes. Finally, the use of the powerful *k-shortest path algorithm* efficiently fitted the trajectory reconstruction.

2. Image processing algorithms for vehicle tracking

Typically, the majority of both static and dynamic observations rely on the same main two tasks of image processing algorithms: identification of moving objects and filtering and classification of the road users of interest (Yilmaz et al, 2006). The border line between these tasks is not always explicit, but in this section we present the general aspects of the main algorithms found in the literature for the trajectory extraction process.

2.1. Background Subtraction

Background subtraction technique is one of the most common methods for motion detection in many object tracking applications. Typically, each image frame is compared against a static background image, using a pixel-by-pixel value subtraction. To build the background image, several methods have been developed, including the frame average method, maximum/minimum intensity value method (Cho and Rice, 2004), median (and approximate median) value method (Remagnino et al, 1997), Gaussian and mixture of Gaussian methods (Magee et al, 2004) and Kalman filtering techniques (Cheung et al, 2004). Background subtraction provides the most complete feature information and a high detection-rate, but the disadvantage of all these techniques is that they are extremely sensitive to dynamic scene changes due to lighting and extraneous events and, sometimes, computationally demanding. Knoop et al (2009), for example, when focusing in car-following trajectory extraction on freeways, selected one line of pixels along each lane centre-line and processed it, shortening processing time.

2.2. Tracking

Feature-based tracking is based on tracking of points which have a particular texture in their respective image positions. These interest points have been long used in the context of motion, stereo, and tracking problems. A desirable quality of an interest point is its invariance to changes in illumination and camera viewpoint. These points (features) are then grouped considering spatial proximity or similar motion patterns along relevant the multiple image frames. These algorithms have distinct advantages over other methods: they are robust to partial occlusions, they don't require initialization, and can adapt successfully and rapidly to variable lighting conditions, allowing real-time processing and tracking of multiple objects (Saunier and Sayed, 2006). However, special requirements have to be met as regards to camera calibration and objects with similar motions (Ismail, 2010).

Another type of tracking approach is based on segmentation algorithms, where images are partitioned into perceptually similar regions (blobs). Frequently, blobs identified in each frame are assign to motion tracks using Kalman filters. Region-based tracking is computationally efficient and works well in free-flowing traffic (Veeraraghavan et al, 2003). However, under congested traffic conditions, vehicles may partially occlude one another, making individual blob identification much more difficult.

Finally, contour-based approaches rely on detecting and tracking a model of the object contour and motion. The vehicle contour is dynamically updated in order to fit the observed vehicle outline. Contour tracking is computationally more efficient than previous vehicle tracking approaches by virtue of the simplicity of describing contour models. Others advantages of using contours is their flexibility to handle a large variety of object shapes, object merge and split. Silhouettes can be represented in different ways. Several successful applications of contour-based tracking may be found in the literature (Yilmaz et al, 2006).

2.3. Supervised learning

Object detection can be performed by learning different object views automatically from a set of examples by means of a supervised learning mechanism. Given a set of learning examples, supervised learning methods generate a function that maps inputs to desired outputs. These learning approaches include neural networks (Goerick et al., 1996), adaptive boosting (Viola et al., 2003) and support vector machines (Papageorgiou and Poggio, 2000).

2.4. Objects filtering

After the moving objects have been identified in all frames, road users are generally selected by knowledge-based or motion-based criteria. Knowledge-based methods employ a prior knowledge to decide whether the identified object is a road user of interest. Features like symmetry, colour, shadow, vertical/horizontal edge, texture descriptors (such as wavelets) and 3D vehicle model are used as classification criteria (Bhattacharya et al., 2011). Motion-based methods use optical flow, a dense field of displacement vectors which defines the translation of each pixel in a region, which is computed using the brightness constraint, assuming brightness constancy of corresponding pixels in consecutive frames (Haag and Nagel, 1999).

In the past years, the first steps on data fusion and estimation of models with trajectory data from different sources have been carried out (Chan and Bougler, 2005). With the continuous development of new and accessible sensoring equipment and its arrival to the telecommunication and vehicle technologies market, it is expected that the collection of behavioural data will be even more efficient through vehicle and site-based data fusion.

3. System Configuration

In the current study, a Cessna T210L Centurion II aircraft, with a gyro-stabilizing platform GSM3000 assuring the support of a Digicam-H/39 camera was used in the image collection. The choice of such method (instead of static observation or more advanced aircrafts) relied on its ability to collect partial trajectories over the entire length of the pilot study area and fulfil existing financial limitations. The Digicam, with a RGB sensor of 7216x5412 pixels and a 80*mm* Hasselblad lens allowed for a very high resolution image collection and was directly connected to a high precision positioning system through differential GPS for flight data collection. Photos were collected at an average rate of 0.5*Hz*, triggered by the fixed maximum image overlapping rate of 90%. The focal distance, shutter speed and aperture were fixed during the entire flight over the study site, the A44 motorway, a 5*km* urban motorway in the southern region of Porto, Portugal.

On the morning of the 11th of October 2011, the aircraft overflew the A44 twelve times, between 7:45 and 12:00 AM, six times in each road traffic direction. The average speed and altitude were 220*km/h* and 2800*m* respectively. These flight characteristics were selected considering the atmospheric conditions and an optimized resolution/coverage of the images, allowing for an average ground sample distance of 23*cm*. The orthorectification of the Digicam images was carried out by InfoPortugal S.A., modelling the terrain in 3D and applying the needed transformations.

4. Image Processing

The image processing procedure is composed by many sub-tasks that may or may not be integrated in a single algorithm, depending on the chosen approach. In our specific case study, a background subtraction approach was used in the detection of moving vehicles. To complete this process, the following steps were carried out:

- local image rectification to account for the terrain model and main orthorrectification errors;
- detection of moving objects;
- filtering vehicles from other objects.

All image processing tasks were carried out with a computer server, holding 48Gb of RAM memory and 16 Intel® Xeon® E620 quad-core processors at 2.4*Ghz*, allowing for a faster computation during the heavy image processing. The code was built in `MATLAB`. It is worth mentioning that the library `OpenCV` is, along with `MATLAB`, one of the most commonly used platforms for image processing. Although this `C/C++` based library might have several advantages, `MATLAB`'s Image Processing Toolbox easy use, interface and memory management were key choice factors for this offline application.

4.1. Local orthorectification

To minimize the errors of each image main orthorectification and 3D terrain model, an automatic local rectification process was used. Each image was divided into grids, scaled and referenced automatically using the SIFT (Scale Invariant Feature Transform) method (Lowe, 2004), an algorithm to detect and describe local features in images. Several applications of the SIFT and similar methods may be found in the literature. Since the matching points between Digicam images must verify the projective model, we used the RANSAC (random sample consensus) algorithm to select the correct matches (Fischler and Bolles, 1981). The reader should refer to both Lowe (2004) and Fischler and Bolles (1981) for details on these two image processing algorithms.

4.2. Background subtraction

For each flight over the A44 a background was constructed using the median filter. The coloured background was computed by taking the 1-D median (in the temporal direction) and computed on all three channels (Red, Green and Blue) separately (see Fig. 1.b)). For each image, the colour similarity metric (Cutler and Davis, 1998) was then used for background subtraction:

$$F(x,y) = \sum_{c\in\{R,G,B\}} |I_c(x,y) - B_c(x,y)| \tag{1}$$

where $I_c(x,y)$ is the value of the pixel (x,y) for colour c of image I, $B_c(x,y)$ is the color value for the same pixel in the background image and $\{R,G,B\}$ are the three colour channels (see Fig. 1.c)). For early flights, when congestion is observed, the background computed for later flights was used for smoothing the background pixel values, as slow/stopped vehicles would bias the median value. Foreground pixels $F(x,y)$ in each grid image were then marked considering a unimodal threshold automatically computed for each image using the maximum deviation algorithm proposed by Rosin (2001). This algorithm is especially suitable to images where a much larger proportion of just one class of pixels (e.g. the background) dominates the foreground histogram. A straight line is drawn from the peak (dominant) to the high end of the histogram. More specifically, the line starts at the largest bin and finishes at the first empty bin of the histogram following the last filled bin. The threshold point is selected as the histogram index bin that maximizes the perpendicular distance between the line and the point on the histogram curve.

5. Vehicle Filtering

After marking all foreground pixels (moving objects), pixels belonging to moving shadows must be filtered out to minimize the errors of the automatic positioning of vehicles. As coloured images were use, this issue was solved using the spectral rationing technique, successfully applied to traffic scenes (Tsai, 2006). First, foreground and background images were transformed into the invariant colour model YCbCr, and the spectral ratio measure was calculated for each pixel:

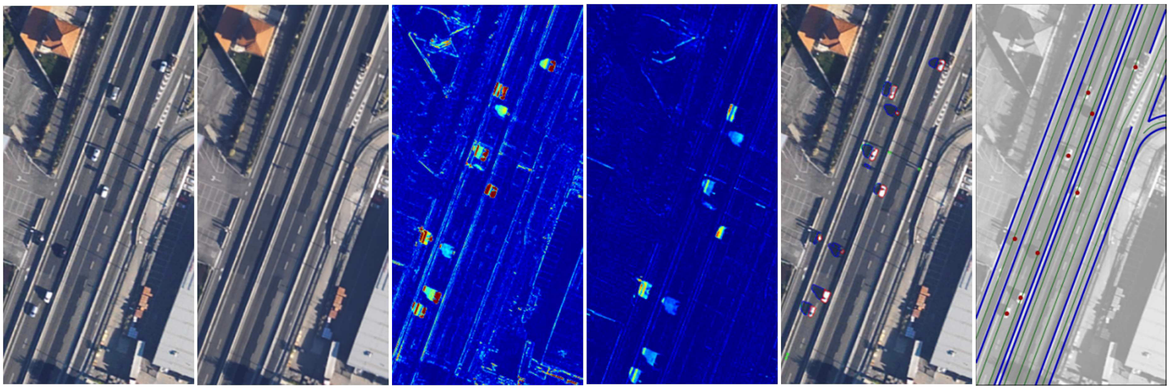
$$S(x,y) = \frac{I_{Cr}^{scaled}(x,y)+1}{I_{Y}^{scaled}(x,y)+1} \tag{2}$$

where $S(x,y)$ is the value of spectral ratio at the pixel (x,y), $I_{Cr\ or\ Y}(x,y)$ is the value of the pixel intensity for the invariant color Y or Cr scaled to $[0,1]$. Shadowed regions, having higher ratio values, were marked into a logical shadow mask (see Fig. 1.d)). The Otsu's method (Otsu, 1979) was used to automatically determine the threshold for segmenting shadow regions in each image grid. Finally, simple morphological operations such as removing isolated pixels and erosion followed by dilation were used for the shadow mask enhancement.

After filtering the foreground for non-shadow pixels, a region-based analysis is performed to extract blobs out of connected pixels in the foreground image (see Fig. 1.e)). These blobs are filtered based on their features: minimum and maximum projected area, minimum and maximum projected width and length and specific shape based relationships:

$$i \in S\ if = \begin{cases} 1.25m^2 < A < 90.00m^2 \\ l_{min} > 1.00m \\ l_{max} < 14.00m \\ \frac{l_{max}}{l_{min}} < 4.15 \\ \frac{A}{l_{max}\times l_{min}} > 0.55 \end{cases} \tag{3}$$

where S is the final set of vehicle candidates. With such method, vehicle-like shape blobs and their characteristics were extracted. It is worth mentioning that the thresholds referred in eq. 3 do not represent typical vehicle geometric features, but the way they are interpreted during the image processing. As an example, the $1.25m^2$ used for the minimum projected area accounts for the possibility of detection of just the car hood in the foreground, due to windshield colour properties in aerial images.



a) original image b) background c) foreground d) spectral ratio e) blob analysis f) position extraction

Fig. 1. Image processing steps

6. Vehicle Tracking

After achieving the time-independent detection of vehicles, the second step relies on linking identified candidate positions into the most likely trajectories. Graph theory has been recently applied to the vehicle tracking problem with success (Berclaz et al, 2011). In such an approach, every region in a frame is represented by a node in the graph. A link between each region in two consecutive frames is generated. Linear Programming (LP) can be used to link multiple detections over time, and therefore solve the graph problem (Song and Nevatia, 2007). However, the computational complexity of the dynamic programming approach can be prohibitive when the frame or/and vehicle number is higher. Recently Berclaz et al (2011) reformulated the LP problem as a k-shortest disjoint paths problem on a directed acyclic graph and solved it using the Suurballe algorithm (Suurballe, 1974). In their study, the areas of interest in the image sequence and the total time interval were discretized and detected object on successive images linked to form possible motion paths, resulting in a directed acyclic graph. Two additional nodes (source and sink) were added to account for a consistent flow of vehicles in the data set. These two nodes are linked to all the nodes representing positions through which objects can respectively enter or exit the study area, such as occlusions or the camera field of view. Any path between the source and sink nodes represent the flow of a single object in the original problem, hence a trajectory (see Fig. 2). The node-disjointness constraint achieved by the Surballe algorithm is needed to assure that no caudate position can be shared between two paths. Finally, in Berclaz et al (2011), the optimization function depends on the marginal posterior probability of the presence of an object in each image. In our current application the information obtained from the segmentation analysis in the vehicle detection task, such as blob area or average blob colour, is error prone due to the small ground sample distance and lighting conditions. The use of such features as main tracking function is not suitable in such conditions.

To overcome this limitation an alternative approach was tested: using dual graphs representing vehicle motion parameters in the optimizing function. First, we limit the set of possible motion parameters characterising a vehicles' path by setting a threshold values for speed, acceleration and deceleration. With this simple step a graph where all acceptable vehicle position candidates' are connected may be constructed. From this graph, speed and acceleration dual graphs may be computed (Winter and Grünbacher, 2002). Typically used to account for turn costs in network graphs, the dual graphs accounts for edge-to-edge cost and, therefore, speeds from the position based graph. Then, we also assumed that any driver has a motion-based optimizing function, i.e., that any trajectory relies on a set of motion-based objectives of the driver. Ideally, complex microscopic driver behaviour models and Kalman-filter dynamics model may be used in this process using large number of motion variables and parameters (gaps, headways, accelerations, etc) to reconstruct trajectories along with the k-shortest disjoint path algorithm. Due to specific nature of the current application a simpler approach was considered. In free-flow conditions, it is known that a driver tends to reach and maintain their target speed. When relaxing the free-flow constrain, one may assume that the driver tends to minimize changes in acceleration. These changes are even smaller if observations are more frequent, due to vehicle dynamics limitations. Regarding lateral movement, a similar approach can be formulated with the inclusion of lane change tags: when the lateral acceleration is constant and different from zero for a longer period of time, a lane change might be tagged for that trajectory. A later paper presenting the details of the vehicle tracking process is expected.

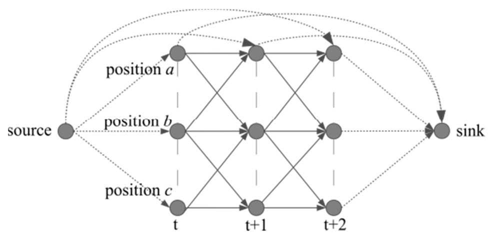


Fig. 2. Graph construction

7. Results

The method presented in this section successfully collected a total of 1855 trajectories for all twelve flights. During the first three flight runs over the A44, congestion was observed in the South-North direction. Levels of service E and F were observed for this subset, which correspond to the 7:45-8:30 AM period. The distribution of key traffic variables were extracted for each flight run for assessment. In Fig. 3, the empirical cumulative distribution functions (CDF) for some of these variables are presented. As expected, speed and headway have a (truncated) normal distribution. It is worth noting that, for the particular flight run presented, low values for speed and headway were still collected in some sections of the A44, resulting in a bimodal nature of their distribution (see Fig. 3 a) and b)). Acceleration and deceleration follow a half-normal distribution with the typical low upper and lower range values for non aggressive manoeuvres. This driving behaviour is also noticeable when looking at the time-to-collision (TTC) and deceleration rate to avoid crash (DRAC) distributions. High and low values for TTC and DRAC, respectively, show typical safe scenarios, with TTC>1.5*s* and DRAC<1m/s^2. The few observed unsafe records and negative gap values are due to vehicle position and length errors in stop and go scenarios.

In Fig. 3 and 4, a set of extracted trajectories in both main lanes in the South-North direction of the A44 motorway for an early flight are analyzed in more detail. Again, the congestion at the end of lane 2 is evident throughout all graphs. Different lane changes may result in different graph changes: a heavy vehicle switches from lane 2 to lane 1 around 3000m, increasing the headway in lane 2 and decreasing the speed on lane 1; a car around 1800m on lane 1 accelerates to overpass the front vehicle, decreasing the TTC in lane 1 and the speed in lane 2, before and after the lane change, respectively.

8. Discussion and Conclusions

In this short paper, a method for automatic extraction of vehicle trajectories was proposed to fulfil the need of detailed traffic variables for microscopic studies. This method allowed for the collection of partial trajectories during one entire morning and for the total extension of the motorway (~5*km*), forming a unique dataset suitable for highway full calibration. Approximately, 95% of the trajectories were successfully extracted even with high temporal and spatial resolutions of 2*s* and 0.25*cm* respectively. Lighting conditions reliability of previous methods was minimized using coloured imagery and advanced spectral filtering while computer vision techniques helped to enhance the image referencing process and reduce its manual work load. The *k-shortest path algorithm* simplified significantly the tracking task, by directly integrating motion criteria in the optimization of the trajectory reconstruction. Its design flexibility brings a strong advantage compared to previous strict motion-based (Kalman filtering) or image-based (feature tracking) approaches. Despite the successful results, three main limitations must be acknowledged, allowing the establishment of method applicability and future enhancements.

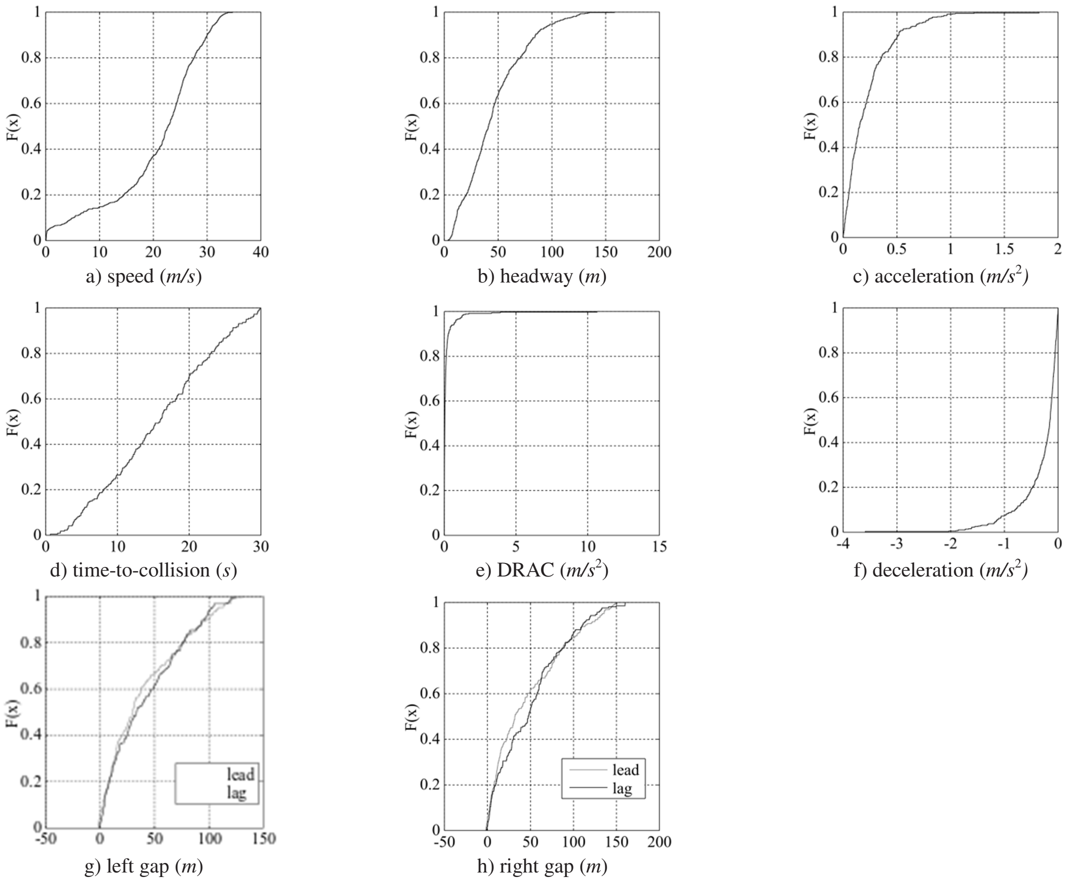
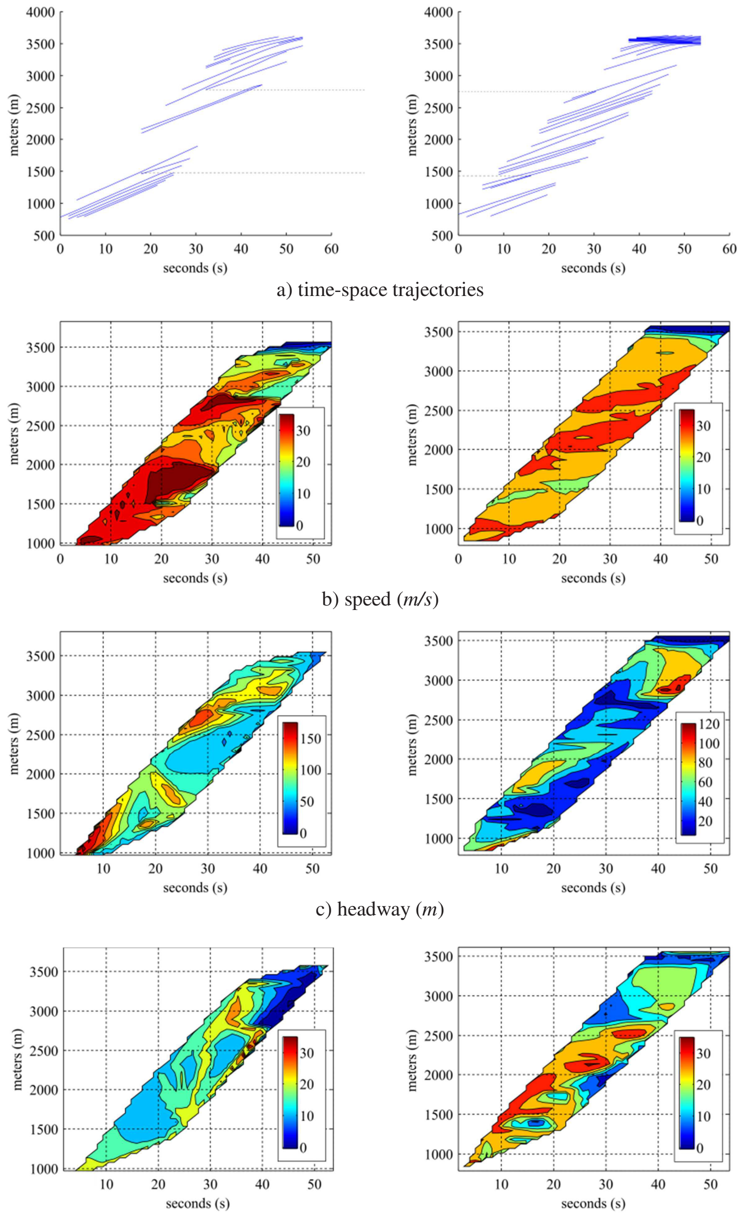


Fig. 3. Empirical CDF of traffic variables

- Inevitably, when opting for traditional and less expensive aircraft instead of helicopters, only partial trajectories are collected due to the dynamic nature of the observation point. Unmanned Aerial Vehicles may bring a much higher flexibility to this process, especially for narrow study areas.
- The available computational resources allowed for the use of simple and robust foreground detection such as the median filter. If such resources are not available, Gaussian mixture models should be consider in the background construction task. The high ground sampling distance still affected the region segmentation and vehicle features extraction. Shadows are always a serious obstacle during the analysis of many outdoor image sets. Although the advanced spectral filter limited errors in the position extraction, it originated false negatives. Dynamic shadow and 3D vehicle models may be found in the literature to minimize these issues. Also, the use of stereo imagery would contribute to avoid these modelling burdens, albeit at a higher cost.



a) time-space trajectories

b) speed (*m/s*)

c) headway (*m*)

d) time-to-collision (*s*)

Fig. 4. Tracking results for lane 1 (left) and lane 2 (right) in the S-N direction of the A44 motorway

- Finally, the original specification of the Suurballe algorithm applied to Dual graphs may not converge to the true optimal solution. This allows for node-joint paths in the final solution of the algorithm. A possible solution is to use an Integer Programming (LP) formulation, as proposed by Berclaz et al (2011), instead of the graph-oriented formulation of Suurballe, assuring that the constraint matrix exhibits a property known as total unimodularity, but at the expense of higher computer processing time, especially under dense traffic conditions. Future work on this topic is expected to bring additional enhancements to the proposed method.

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