A CAMERA AUTO-CALIBRATION ALGORITHM FOR REALTIME ROAD TRAFFIC ANALYSIS

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Abstract: This paper presents a new mono-camera system for traffic surveillance. It uses an original algorithm to obtain automatically a calibration pattern from road lane markings. Movement detection is done with a $\Sigma - \Delta$ background estimation which is a non linear method of background substraction based on comparison and elementary increment/decrement. Foreground and calibration data obtained allow to determine vehicles speed in an efficient manner. Finally, a new method to estimate the height of vehicles is presented.

1 INTRODUCTION

Road traffic is increasing each year. Understanding its characteristics is very helpful to motorway administrators to cope with this growth, and achieve regulations. Among traffic characteristics, user behaviours and classes of vehicles are the most relevant.

Until a few years ago, the main measurement tool for traffic analysis was the magnetic inductive loop. That kind of sensors has serious drawbacks: it is expensive to install and maintain. Indeed, it needs to be placed inside the road, provoking traffic disruption. Furthermore, it is unable to detect slow or stationary vehicles, being not accurate for stop and go situations.

On the other side, video sensing is a good solution since it is inexpensive, easy to install and able to cover a wide area. Furthemore, it has little traffic disruption during installation or maintenance. Finally, video analysis allows monitoring many variables such as traffic speed, vehicle count, vehicle class and road state.

Most of the existing video solutions are based on mono-camera systems. A state of the art can be found in (Kastrinaki et al., 2003). Among all the methods, background methods are the most used since they demand small computational power and are simple to program. In such method, a residual image is obtained from substracting the background from the current image (jun Tan et al., 2007). Other solutions use tracked features, see (Dickinson et al., 1989) and (Hogg et al., 1984).

In this work, a new mono-camera method for traffic analysis is presented. It uses an original algorithm to obtain automatically a calibration pattern from road lane markings. Movement detection is done with a $\Sigma - \Delta$ background estimation. It is a non linear method of background substraction based on comparison and elementary increment/decrement (Manzanera, 2008). Foreground and calibration data obtained allow to determine vehicles speed in an efficient manner. Finally, a new method to estimate the height of vehicles is presented.

This paper is organized as follows: section 2 presents the auto-calibration algorithm. Methods used to estimate vehicle characteristics are discussed in section 3. Experiment results are depicted in section 4 and finaly, section 5 ends this paper with the conclusion.

2 CAMERA AUTO-CALIBRATION

Road traffic analysis needs a calibrated camera. However, a camera calibration is performed by observing a calibration object whose geometry in 3D-space is known with good precision. In order to avoid the use of special object of known geometry such as chessboard, which implies to stop road traffic during operation, the adopted solution is to form a calibration pattern from the road lane markings. To do that, two parameters are necessary: the lane length and width. Based on these values, the algorithm presented in this

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section determines automatically a good calibration pattern.

2.1 Camera Model

The camera model we use is the one proposed in (He and Yung, 2007) and (Fung et al., 2003), which is depicted in figure 1. This model describes one intrinsic parameter (focal length f) of the camera and all its extrinsic parameters (height h, pan angle p, swing angle s and tilt angle t), and defines the relationship between the image coordinates and the world coordinates in terms of these parameters.

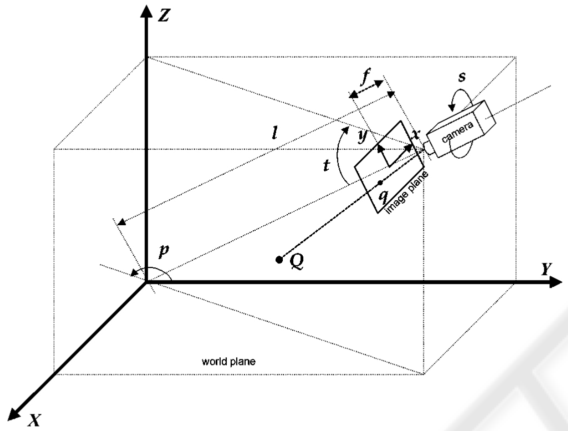


Figure 1: Used camera model (He and Yung, 2007).

Let $\mathbf{Q} = (X_Q, Y_Q, Z_Q)$ be an arbitrary point in the 3D world coordinates and $\mathbf{q} = (x_q, y_q)$ be the corresponding 2D image coordinates of $\mathbf{Q}$. The equations that relate these two points are

$$x_q = \frac{f \begin{bmatrix} X_Q\,(cos\,p\,cos\,s + sin\,p\,sin\,t\,sin\,s) \\ +Y_Q\,(sin\,p\,cos\,s - cos\,p\,sin\,t\,sin\,s) \\ +Z_Q\,cos\,t\,sin\,s \end{bmatrix}}{-X_Q\,sin\,p\,cos\,t + Y_Q\,cos\,p\,cos\,t + Z_Q\,sin\,t + h/sin\,t} \tag{1}$$

and

$$y_q = \frac{f \begin{bmatrix} X_Q\,(-\,cos\,p\,sin\,s + sin\,p\,sin\,t\,cos\,s) \\ +Y_Q\,(-\,sin\,p\,sin\,s - cos\,p\,sin\,t\,cos\,s) \\ +Z_Q\,cos\,t\,sin\,s \end{bmatrix}}{-X_Q\,sin\,p\,cos\,t + Y_Q\,cos\,p\,cos\,t + Z_Q\,sin\,t + h/sin\,t}. \tag{2}$$

If we assume that point $\mathbf{Q}$ lies on the X-Y plane then Z_Q becomes zero and (X_Q, Y_Q, Z_Q) can be calculated from (x_q, y_q) as:

$$X_Q = \frac{\begin{bmatrix} h\,sin\,p\,(x_q\,sin\,s + y_q\,cos\,s)\,/\,sin\,t \\ +\,h\,cos\,p\,(x_q\,cos\,s - y_q\,sin\,s) \end{bmatrix}}{x_q\,cos\,t\,sin\,t + y_q\,cos\,t\,cos\,s + f\,sin\,t} \tag{3}$$

and

$$Y_Q = \frac{\begin{bmatrix} -\,h\,cos\,p\,(x_q\,sin\,s + y_q\,cos\,s)\,/\,sin\,t \\ +\,h\,sin\,p\,(x_q\,cos\,s - y_q\,sin\,s) \end{bmatrix}}{x_q\,cos\,t\,sin\,t + y_q\,cos\,t\,cos\,s + f\,sin\,t}. \tag{4}$$

These four equations define the transformation between the world coordinates and image coordinates, knowing the camera parameters. To estimate these parameters, a calibration pattern of known dimensions is necessary. Next section describes the procedure used to get it.

2.2 Finding a Good Calibration Pattern

The desired calibration pattern is based on the road lane markings. The first thing needed to automatically find such a calibration pattern is a good image of the road to work with. Typically, the background image is a good solution.

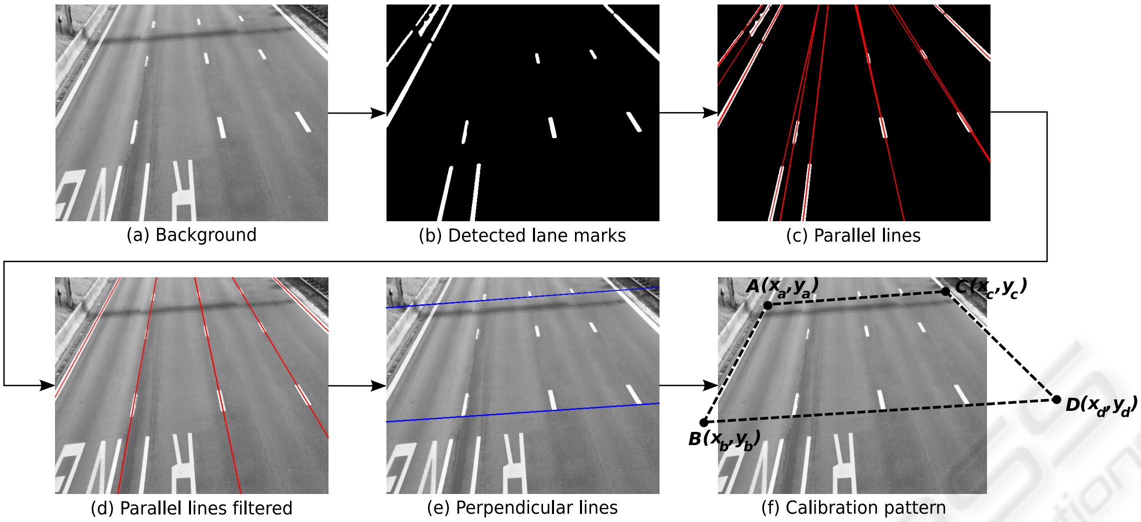
2.2.1 Background Image

The method used is based on the $\Sigma - \Delta$ filter and belongs to the substraction technique (Manzanera, 2008). Its operating principle is to calculate a temporal and local activity map, in order to define automatically the thresholds used to decide if a pixel belongs to the background or to the foreground, these thresholds being variable spatially and temporally (see figure 2a).

2.2.2 Lane Markings Detection

Parallel Lines. First of all, the assumption that lane markings are almost parallel to each other and approximate straight lines is made.
To detect lane markings, a filter is applied many times to the background image, but with different parameter values. This filter determines pixels whose neighborhood (first parameter) is brighter than itself with a certain tolerance (second parameter). The resulting images obtained with this filter will then be processed. For each image, a label is assigned to each binary connected components and some of their shape properties are measured (i.e. the surface, eccentricity, orientation and centroid). Once this has been done, the properties of the obtained groups in each image are compared. The ones with more or less stable properties in all the images are kept. Finally, the groups that do not comply with certain constraints are rejected. The remaining groups correspond to various objects considered as possible lane markings (see figure 2b).

After that, one virtual line is created per detected object, each line passing through the centroid and



(a) Background (b) Detected lane marks (c) Parallel lines

(d) Parallel lines filtered (e) Perpendicular lines (f) Calibration pattern

Figure 2: Calibration pattern algorithm.

having the same orientation as its corresponding object (figure 2c). These virtual lines are called *parallel lines*.

These parallel lines are filtered to retrieve the ones corresponding to real lane markings (see figure 2d). The filtering process has three steps. The first one consists in merging parallel lines whose centroids and orientation are fairly close. The second step is based on the neighborhood of each parallel line. For each parallel line, the neighborhood in the background image is analysed to find bright objects and count them. Any parallel lines for which too few objects were found are deleted. Finally, the last step checks the distance between parallel lines and rejects bad ones. Once all of this has been done, parallel lines are obtained.

Perpendicular lines. Once the parallel lines have been detected, finding perpendicular lines can be done easily. Pixel brightness along every parallel line is analysed to find the beginnings and ends of lane markings along that line. Depending on the situation, two methods can be used to find perpendicular lines. The first one works only on roads with at least three lanes while the second one works on roads with at least two lanes.

For the first method, it is assumed that discontinuous lane markings are more or less synchronous in the 3D space. Starting from this assumption, the parallel lines detected before are analysed to find lane markings. Then, virtual lines passing through the corresponding lane markings of each parallel line are created, as shown in figure 2e. These virtual lines are called *perpendicular lines*.

For a two lanes road, there are only two continuous lane markings on the edge of the road and one discontinuous lane marking in the middle. A perpendicular line is obtained by taking a point (called *pivot point*) on the parallel line passing through the discontinuous lane marking. The traffic is then analysed to find near perpendicular lines on vehicles with the assumption that they are travelling along road axis. Each time such a line is detected passing near a pivot point, its orientation is used to adjust the perpendicular line passing through that pivot point, as shown in figure 3.

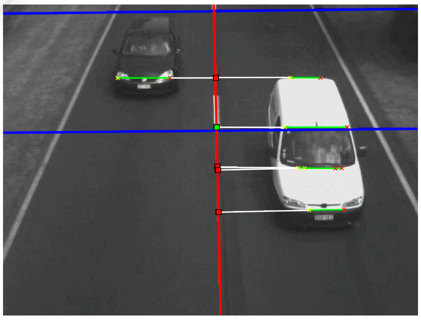


Figure 3: Perpendicular lines on a two lanes road.

2.2.3 Calibration Pattern

After the lane markings detection, intersections of parallel and perpendicular lines are calculated and the four points farthest from each other are kept. These points form the parallelogram used as *calibration pattern* to calibrate the camera, as shown in figure 2f. The reason why a calibration pattern as large as possible is desired is that it helps minimize the error due to poor positioning points.

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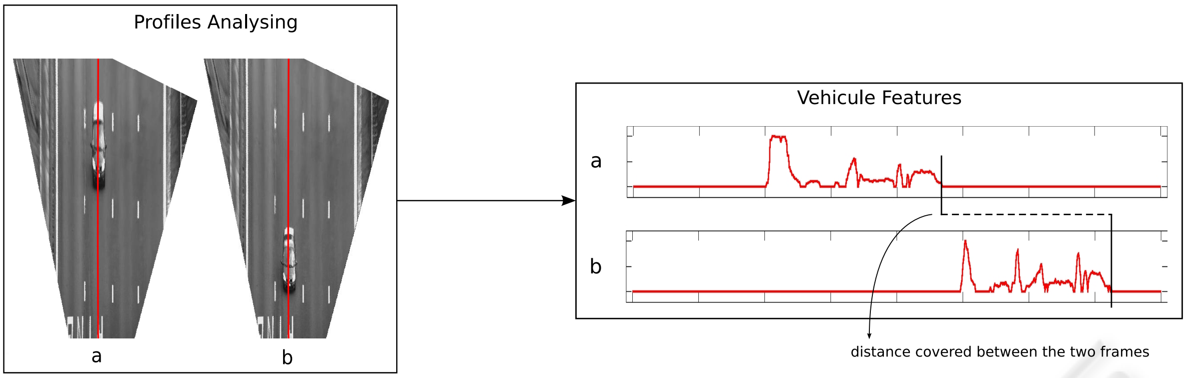

Figure 4: Features extraction from two consecutive frames *a* and *b*.

2.3 Camera Calibration

Once a good calibration pattern is found, the camera parameters are estimated with the method proposed in (He and Yung, 2007). The equations (3) and (4) are then used to project the images on the $X-Y$ plane of the 3D world ($Z_Q = 0$), as shown in the figure 5.

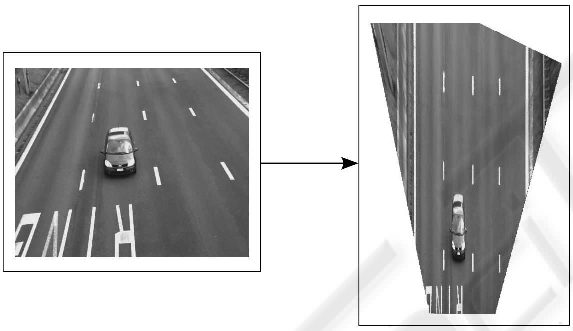

Figure 5: Image projection.

3 VEHICLE FEATURES EXTRACTION

Extracting vehicle features implies detecting the traffic. A common way to do this is to subtract the background image (see section 2.2.1) from the current frame to get a foreground image. In this approach, instead of working with the whole image, virtual lines called *profile* are used. Figure 4 shows an example of one profile analysis. For the sake of clarity, just one profile is shown in this example but, of course, as many profiles as necessary can be defined. Typically, five profiles per lane is quite sufficient.

3.1 Speed Estimation

Once features of a vehicle have been extracted from two frames, estimating its speed by measuring the distance between the beginning of its signal in successive frames is possible, as shown in figure 4.

3.2 Height Estimation

Based on the deformations visible on vehicle profile (due to the perspective effect), estimating the height of this vehicle is possible. Indeed, the equations (3) and (4) used for the transformation from image coordinates to world coordinates project the images on the *X*-*Y* plane of the 3D world. This implies two things. First, the more a point is high above the ground, the more its distance from the camera will be overestimated. And second, the more a point above the ground is far away from the camera, the more its distance from the camera will be over-estimated too. So, a relation between the height of a vehicle and the deformation of his profile from a frame to another can be found.

Figure 6 shows what happens when a car (represented here by a box) approaches the camera. Because the points A and B are known, distance c can be calculated. Then, through the tilt angle of the camera, angles $\widehat{A}$ and $\widehat{B}_2$ are obtained, wich leads to $\widehat{B}_1$ and $\widehat{C}$. Finaly, using the classical law of sines

$$\frac{a}{sin\widehat{A}} = \frac{b}{sin\widehat{B}} = \frac{c}{sin\widehat{C}} \qquad (5)$$

length a and height h of the vehicule are found.

4 EXPERIMENTAL RESULTS

To validate the features extraction and the speed estimation method, a test was conducted on a video sequence. The results are presented in table 1. For your

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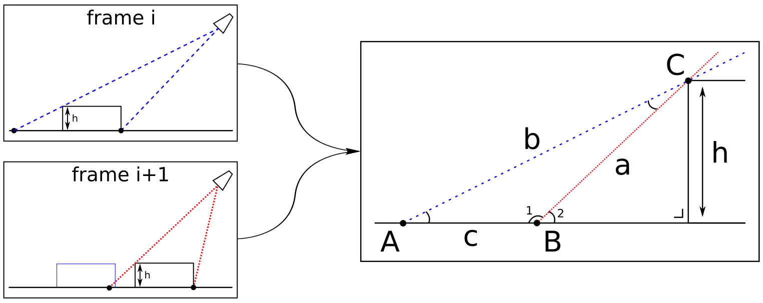

Figure 6: Vehicle height estimation.

information, the last value *one pass* corresponds to the estimated speed, using only the first and the last frame (i.e. the first frame in which the vehicle is visible and the last one in which it is still visible). Unfortunately, these results could not be validated for lack of radar measures. However, they ensured us that the estimated speed was consistent compared with the video sequence.

Table 1: Estimation speed results (in km/h).

frame id	lane 1	lane 2	lane 3
1	0	0	0
2	107	0	0
3	99	0	0
4	104	0	0
5	107	0	0
6	99	0	0
7	102	0	0
8	104	110	0
9	99	107	0
10	107	107	102
11	102	110	107
12	104	107	102
13	104	107	107
14	104	110	104
15	104	107	102
16	104	110	107
17	110	107	104
18	0	112	104
19	0	102	104
20	0	115	107
21	0	112	107
22	0	112	104
23	0	0	112
24	0	0	0
mean	104	109	105
median	104	110	104
one pass	104	109	106

To validate height estimation method, a chessboard with known dimensions is used to calibrate the camera. Then, two pictures of moving objects on the chessboard are taken. Finally, the height of these objects is estimated. Table 2 shows that results have an estimation error of less than 3%.

Table 2: Estimation height results (in mm).

frame id	object 1	object 2	object 3
1	81.96	42.48	100.66
2	82.63	41.07	99.01
3	79.18	41.43	100.24
4	78.06	42.13	99.46
mean	80.46	41.78	99.84
real	81	43	100
error	0.6%	2.8%	0.2%

5 CONCLUSIONS AND FUTURE WORK

In conclusion, a mono-camera system for traffic monitoring that can accurately and automatically calibrate itself has been presented. It detects all the vehicles and estimates their speed, and because it doesn't need all the image pixels to work, it is quite efficient. Additionally, a method to estimate vehicle height has been presented which, according to first tests, should operate relatively well. Furthermore, once the vehicle height will be known, estimating its width and length will be possible.

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