Road Traffic Mean Speed Estimation Using a Camera

Mohammed Abdessamad Bekhti, Belal Abdelaziz Ibrahim Alshaqaqi
University of Science and Technology of Oran Mohamed Boudiaf
Faculty of Electrical Engineering, Department of Electronics
Signal and Image Laboratory
Oran, Algeria
bmabdessamed@gmail.com, alshaqaqi@ieee.org

***Abstract*—Embedded systems become more and more present in our daily life. The validation of this kind of systems with time their evolution became fast and complex we focus on multiprocessor systems on chip (MPSoC) and exactly Qaulity of Service of Network on chip architecture (QNoC). The interconnection of communication modules (IP - Intellectual Property) constitutes a fundamental part during the design of such systems expressed in terms on band-width, latency, power consumption and reliability. The validation currently for MPSoC (with QNoC's basis) based on the logical simulation which it can't allow a global validation for this system even it is not adapted for the design of high level integration complex systems (Handicaps with respect to the concept *time to market*).**

Keywords- Intelligent Transportation Systems, object detection, object tracking, data fusion, distance and speed measurement, vehicle countin.

Introduction

Traffic planners around the world are facing great challenges in the design of intelligent transportation systems of the future. Transport demand will continue to increase; reducing traffic congestion, air pollution and the number of accidents will always be the greatest concern. Performance of intelligent transport systems is crucial for the possibilities for individual mobility, business, and economic growth of a nation. An intelligent transportation system operates according to internal procedures to perform defined tasks, among them, vehicle detection, vehicle tracking, and speed measurement. The first step in almost every video surveillance systems is the detection of moving objects. The object detection is the segmentation of the regions corresponding to moving objects from the rest of the image. Subsequent processes such as object tracking depend strongly. A mistake made at this stage is difficult to correct in the following steps. Several approaches exist for detection, among them, those based on characteristics such as symmetry in [1, 2], color in [3], shadow in [4], corners in [5], vehicle lighting in [6], and texture in [7]. Others approaches are based on stereo vision as in [8, 9], while others are based on movement estimation [10]. The system proposed here is based on background subtraction for the detection of vehicles. Among the techniques used, we find the basic background subtraction in [11], the technique known as instantaneous background in [12], and the mixture of Gaussian in [13, 14].

In general, the aim of object tracking is to establish a correspondence between objects or parts of objects between successive frames to extract consistent time information about objects such as trajectory, posture, speed and direction. Among the approaches for tracking vehicles, there are those based on active contours [15, 16]. One technique is the Mean Shift algorithm introduced in [17] and modified for the purpose of tracking. As part of the dynamic approaches, the use of adaptive filters, such as using the algorithm RLS (Recursive Least Square) for vehicle tracking in [18]. In [19], a matching technique is used.

The rest of the paper is organized as follows. In section 2, the block diagram of the vision-based system is introduced. The major steps performed by the system will be discussed in detail in subsequent sections, including road modeling in Section 3, the detection of vehicles in Section 4, vehicle tracking in Section 5, data fusion in section 6, and finally the distance measurement in Section 7. After that, the experimental results will be introduced in Section 8. Concluding remarks are presented in Section 9.

vision based system for measuring distance and road traffic speed

The vision-based system for measuring the speed of the traffic proposed here consists of a camera, a computer, and a number of communications devices. The camera produces a continuous acquisition from a road. The video sequences are transmitted through the Internet to an FTP server where data are stored. The video sequences are processed at the computer level.

The camera can be installed on a bridge, or a higher pole. Figure.1 describes the configuration of the camera. Many parameters of the camera setup are given in the figure, including the tilt angle $\boldsymbol{\theta}$, the height $\boldsymbol{h}$ of the camera. The parameters $\boldsymbol{\theta}$, $\boldsymbol{h}$, and the focal distance of the camera are known in advance.

A block diagram of the proposed vision-based system is presented in Figure. 2. Five major steps constitute the diagram, and are, modeling of the road, vehicle detection, vehicle tracking, data fusion, and speed measurement. The five steps are discussed in the following sections.

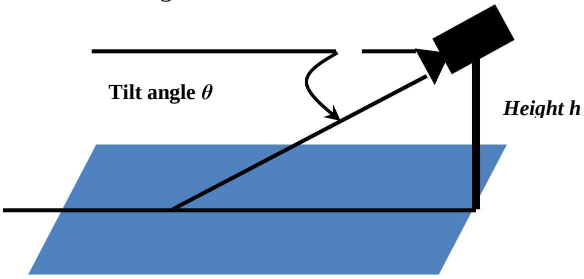

Figure. 1. Camera configuration.

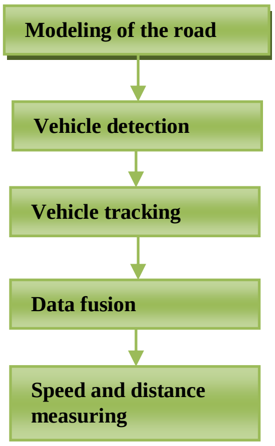

Figure. 2. Diagram of the vision based system.

modeling of the road

Modeling of the road is to extract the lines delimiting it and calculate their equation. This is done by the Hough transform. Data from this step will be used during the speed measurement. It begins by dividing the image scene into two scenes left and right, and apply to the latter the Hough transform. The result is given in Figure. 3.

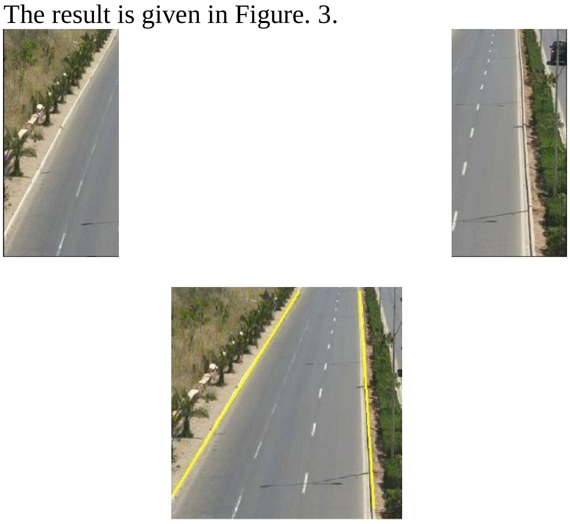

Figure. 3. Road modeling using Hough Transform

detection of vehicles

In our case, the vehicle detection is based on the median filtering technique as in [20]. Let $I_n(x)$ the pixel intensity observed at position x at time n, and $m_n(x)$ the median estimate of the current background at the same position and time. The median approximation $m_{n+1}(x)$ is given as follows in equation (1):

$$m_{n+1}(x) = \begin{cases} m_n(x)+\alpha, & si\ I_n(x) > m_n(x) \\ m_n(x)-\alpha, & si\ I_n(x) < m_n(x) \\ m_n(x), & si\ I_n(x) = m_n(x) \end{cases}$$

(1)

Where α, whose value is between 0 and 1, is assigned according to the convergence rate desired. A pixel $I_n(x)$ is classified as stationary if it satisfies equation (2):

$$\left| I_n(x) - m_n(x) \right| < T$$

(2)

T is the threshold.

The result of this step is given by Figure.4 in (a), (b) and (c).

Generally, there is the presence of impurities, additional unwanted detections. To overcome these problems, morphological adjustments are applied to the object mask. The operation in question is opening, i.e., an erosion followed by dilation. The result is given in Figure. 4 (d). Although the opening ensures properly offset the problems mentioned above, there may be noise that still persists, and therefore confusion between moving objects and the latter. To minimize this effect, an object selection is made to retain only the objects of interest. The object selection consists in carrying out a labeling of the mask.

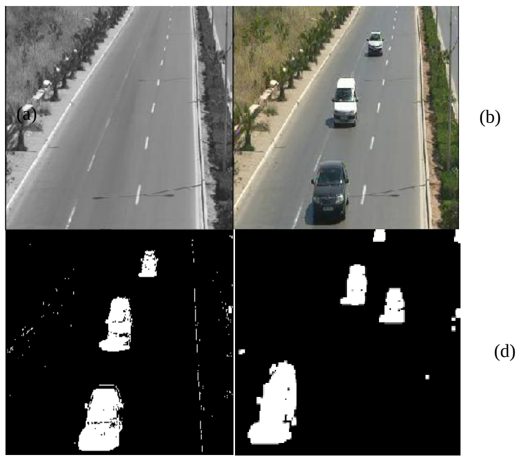

Figure. 4. Object segmentation by median approximation. (a) Estimated background, (b) Current frame, (c) Object mask, (d) Morphological operations.

After this, we calculate the number of pixels per lob. Only the lobs including a number of pixels satisfying a threshold are selected for further processing. Figure.5 (a) shows the result of object selection.

vehicle tracking

The detected vehicles are tracked throughout the video sequence. To do this, the technique used is the search for agreement between the vehicles of each pair of successive images via corresponding more known as Matching.

Figure. 5. (a) Localisation des véhicules, (b) Suivi des véhicules par mise en correspondance.

This correspondence is based on the assessment of similarity by the correlation criterion. In this case, the correlation criterion chosen is the Sum of the Squares Differences (Sum of Squared Differences) given by equation (3). The result is given in Figure.5 (b).

$$SSD = \sum_{(i,j)\in F} (I_1(i,j) - I_2(i+x, j+y))^2$$

(3)

data fusion

In the literature, we have seen that sometimes the authors associate two types of tracking algorithms to improve the result obtained when tracking objects. In this case, we found ourselves facing the problem of whether the tracking result is to some extent correct? In what follows, we will introduce the proposed solution for verifying the results of tracking. At time t, there are two crucial data, namely object detection and tracking of objects from the detection at time t-1. The aim is to be able to establish a relationship between these two information. Figure.6 introduces the principle of the approach.

L'opération de la fusion des données de détection et de suivi va permettre :

- **Répertorier les objets détectés à l'instant t selon trois catégorie, qui sont :**

  - Category 1: an object in processing, i.e. that the object in question is still being tracked because it always appears in our field of vision. This category will gather all correspondence between the results of tracking and detection. This case is illustrated in the figure above by the arrows numbered 1 and 2.

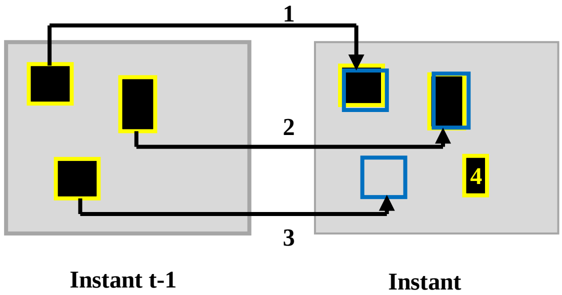

Figure. 6. Data fusion idea.

  - Category 2: This category will list the main results of the tracking to which there is no corresponding detection. This case is encountered in two situations: first, poor detection leading that the object to be detected does not appear. The second, an object that is no longer in the area of interest. This case is shown in Figure above by the arrow 3.

  - Category 3: any object from detection to which there is no correspondence among the tracking result is found. This case is shown in the figure by the object numbered 4.

- Assigning an identifier for objects of class 3, and inserting them into an identification table.

distance and speed measuring

Figure.7 illustrates how to calculate the distance from the road width. The two solid yellow lines represent the lower boundary of the object at times t_1 and t_2. Computing the points of intersection of the line located at the lower boundary of the object with the two straight lines defining the road. The width of the road at that time is equal to the difference of the vertical component of the two points. Equation (4) give the width of the road at times t_1.

$$T_1 = |j_1 - j_2| \quad (4)$$

The distance of the object at the instant t_1 is given by equation (5):

$$D_1 = f\frac{T_r}{T_1} \quad (5)$$

Where T_r represents the width of the road in meters and is fixed, and f is the focal distance of the camera.

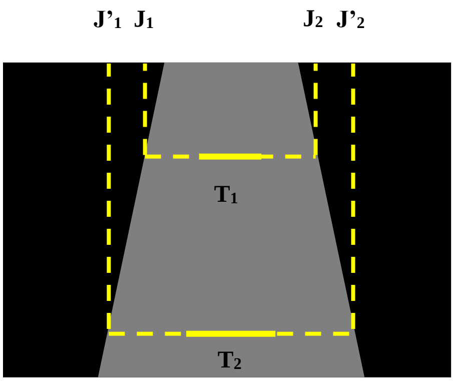

Figure. 7. Distance evaluation from road width.

experimental results

For a good discussion of the technique used for distance measurement, it is proposed to draw three horizontal lines on the image, and each line is given the estimated distance of the object relative to the camera. This operation is performed for three different vehicles.

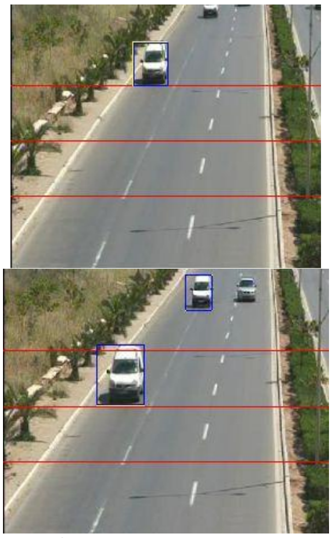

Figure.8. Procedure for validating distance evaluation results.

Table 1 introduces the test results, and Figure. 8 illustrates the method mentioned above.

TABLEAU 1: Distance measurement from the road width test results.

Test number	Distance of vehicle 1 (m)	Distance of vehicle 2 (m)	Distance of vehicle 3 (m)
1	39.13	38.41	39.13
2	29.43	29.71	30
3	24.13	24.23	24.13

In what follows, we propose to validate the accuracy of the results obtained above using sequences that were recorded in the University of Science and Technology, Mohammed Boudiaf Oran. The sequence was taken using an analog CCD camera, and vehicles that appear in the field of vision are moving at a constant speed of 20 km / h. Figure.9 shows the driving speed by two vehicles. The following table introduces the counting result.

Figure. 9. Mean speed estimation results.

TABLEAU 2 : validating results of vehicle counting

Sequence number	Number of frames per sequence	Real number of vehicles	counting
1	1300	5	5
2	2253	25	25
3	1565	17	19

interpretation of results

- In our case, the detection has a direct influence on the measurement of speed and vehicle counts. One solution is to ignore the false detections, for this it is compulsory that a detected object appear for a period longer than 1 second, i.e. at least 30 images.
- Objects taken into account when processing are belonging to a size interval [T_{min}, T_{max}], where T is the number of white pixel (part of the foreground). In this study case, T_{min} is equal to 650 pixels and T_{max} is equal to 1000 pixels.
- In practice, an object that moves must change size and position. In our implementation, for two successive images sometimes the object does not change size, consequently, the speed is influenced. One solution is to increase the resolution of the image and / or a lower image frequency.

conclusions and outlook

In this paper, we present a vision based system for measuring speeds and vehicle counts. The system relies on the use of a camera, a computer for processing, and a number of devices for communication, and installation. Several techniques such as detection lines for the delimitation of the road, the progressive generation of the background image, followed by the matching technique for object tracking, data fusion to manage objects between successive frames, and estimation of speed. The sequences from our camera were used in various experiments. The system provides very satisfactory results under different climatic conditions. It is intended to improve the system by incorporating shadow eliminators and concealment for vehicles, a classifier for the categorization of vehicles, and the possibility to operate by night time.

References

[1] A. Kuehnle, "Symmetry-Based Recognition for Vehicle Rears," *Pattern Recognition Letters,* vol. 12, pp. 249-258, 1991.

[2] M. B. A. Bensrhair, A. Broggi, P. Miche, S. Mousset, and G.Moulminet, "A Cooperative Approach to Vision-Based Vehicle Detection," *IEEE Intelligent Transportation Systems,* pp. 209 - 214, 2001.

[3] S. D. Buluswar and B. A. Draper, "Color Machine Vision for Autonomous Vehicles," *Int'l J. Eng. Applications of Artificial Intelligence,* vol. 1, pp. 245-256, 1998.

[4] C. Tzomakas and W. v. Seelen, "Vehicle Detection in Traffic Scenes Using Shadows," *Technical Report 98-06, Institutfu for Neuroinformatik, RuhtUniversitat, Bochum, Germany,* 1998.

[5] M. Bertozzi, A. Broggi, and S. Castelluccio, "A Real-Time Oriented System for Vehicle Detection," *J. Systems Architecture,* pp. 317 - 325, 1997.

[6] R. Cucchiara and M. Piccardi, "Vehicle Detection under Day and Night Illumination," *Proc. Int'l ICSC Symp. Intelligent Industrial Automation,* 1999.

[7] T. Kalinke, C. Tzomakas, and W. V. Seelen, "A Texture-Based Object Detection and an Adaptive Model-Based Classification " *Procs. IEEE Intelligent Vehicles Symposium,* pp. 143 - 148 1998.

[8] Y.-C. Lin, C.-C. Lin, L.-T. Chen, and C.-K. Chen, "Adaptive IPM-based lane filtering for night forward vehicle detection," *6th IEEE Conference on Industrial Electronics and Applications (ICIEA), 2011* pp. 1568 - 1573, 2011.

[9] Y. Li, G. Toulminet, and A. Bensrhair, "Vehicle detection based on the stereo concept of (axis, width, disparity) symmetry map," *IEEE ITSC - International Conference on Intelligent Transportation Systems,* pp. 778 - 783, 2008.

[10] M. Bertozzi and A. Broggi, "GOLD: A Parallel Real Time Stereo Vision System for Generic Obstacle and Lane Detection," *IEEE TRANSACTIONS ON IMAGE PROCESSING,* vol. 7, 1998.

[11] D.Hall, J. Nascimento, P. Ribeiro, E. Andrade, P. Moreno, S. Pesnel, T. List, R. Emonet, R. B. Fisher, J. S. Victor, and J. L. Crowley, "Comparison of target detection algorithms using adaptive background models," *INRIA Rhone-Alpes, France and IST Lisbon,Portugal and University of Edinburgh,UK,* pp. 585 – 601, 2005.

[12] S. Gupte, O. Masoud, R. F. K. Martin, and N. P. Papanikolopoulos, "Detection and Classification of Vehicles," *IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS,* vol. 3, pp. 37 - 47, 2002.

[13] C.Stauffer and W. E. L. Grimson, " Adaptive background mixture models for real time tracking," *IEEE Computer Society Conference on Computer Vision and Pattern Recognition,* vol. 2, 1999.

[14] T. Yu-min and W. Xiao-tao, "A Fast Convergent Gaussian Mixture Model in Moving Object Detection with Shadow Elimination," *International Conference on E-Product E-Service and E-Entertainment (ICEEE),* pp. 1- 4, 2010.

[15] L. Ying-hong, P. Yi-gui, L. Zheng-xi, and L. Ya-li, "An Intelligent Tracking Technology Based on Kalman and Mean Shift Algorithm," *Second International Conference on Computer Modeling and Simulation,* vol. 1, pp. 107-109, 2010.

[16] D. Keller, J. Weber, T. Huang, J. Malik, G. Ogasawara, B. Rae, and S. Russell, "Towards robust automatic traffic scene analysis in real time," *ICPR,* November 1994.

[17] D. Comaniciu, V. Ramesh, and P. Meer, "Real-time tracking of non-rigid objects using mean shift," *Proceedings of the IEEE conference on computer vision and pattern recognition, Hilton Head, SC,* vol. 2, pp. 142–149, 2000.

[18] H. S. Yazdi, M. Lotfiza, E. Kabir, and M. Fathy, "Clipped Input RLS Applied to Vehicle Tracking," *EURASIP Journal on Applied Signal Processing,* vol. 8, pp. 1221–1228, 2005.

[19] X. C. He and N. H. C. Yung, "A Novel Algorithm for Estimating Vehicle Speed from Two Consecutive Images," *IEEE Workshop on Applications of Computer Vision (WACV'07),* p. 12, 2007.

[20] Z. He, Y. Liu, H. Yu, and X. Ye, "Optimized Algorithms for Traffic Information Collecting in an Embedded System," *Congress on Image and Signal Processing,* vol. 4, pp. 220-223, 2008.