3rd International Conference On Innovation In
COMPUTER SCIENCE & ARTIFICIAL INTELLIGENCE

AMSTERDAM,NETHERLANDS 23-25 OCTOBER, 2020

Intelligent Transport System for the Prevention of Road and Highway Accidents

Bencheriet Chemesse Ennehar[1,*], Boukemoum Zakaria[2] and Menai Mohammed [3], Belhaddad Samir [3]

[1]LAIG laboratory, 8 Mai 1945 University, of Guelma, Algeria

[2]8 Mai 1945 University, of Guelma, Algeria

[3]8 Mai 1945 University, of Guelma, Algeria

Abstract.

Intelligent transportation systems become in recent years a research field of primary importance for the scientific community and for public authorities this interest mainly due to the number of deaths caused each year by road accidents. The main objective of this work consists of detection and tracking vehicles (mainly cars) in road and highway using HOG features and kalman filter. At first, Histogram of Oriented Gradient (HOG) is used to extract feature vectors. Thereafter, a dataset composed by HOG feature vectors of positive and negative examples will be used in SVM (Wide Margin Separators) training. The model obtained after training will allow us to classify the objects detected in vehicles / non-vehicles. For the tracking of detected vehicles, a motion model based on adaptive kalman filter is established. Experiments show that the combination of HOG features and Kalman filter considered as collaboration of a good feature descriptor and a good motion predictor gave good results regarding the cars detection and tracking also the prediction of Kalman filter model provides a reliable region for eliminating the interference of shadows and sharply decreasing the false detection rate.

Keywords: Vehicle detection, Vehicle tracking, HOG features, SVM classifier, Kalman filter.

1. Introduction

With the widespread use of surveillance cameras, motion analysis in videos has proven to be an indispensable tool for diverse applications as road safety, vehicle tracking and event identification or particular behaviors such as non-compliance with safety rules.

info@icaiconf.org www.icaiconf.org

Intelligent Transport Systems (ITS) are part of our daily lives and are the future of modes of transport. They allow solutions for problems like improving road safety and solving the problem of traffic congestion.

ITS considered as sector excellence in many developed countries remains a timid development sector in our country despite the predominant congestion and road safety problems. Vehicle detection and tracking applications play an important role for many applications such as in highway traffic surveillance control management and traffic planning. (Shukla & Saini, 2015), Presents a review on the various techniques of On-Road Vehicle detection systems that are based on motion model.

Other study (Wang et al., 2016) based on a collaborative fusion approach to achieve the optimal balance between vehicle detection accuracy and computational efficiency. In (Tian et al., 2014) authors propose rear-view vehicle detection and tracking method based on multiple vehicle salient parts using a stationary camera. Vehicle is treated as an object composed of multiple salient parts. These parts are localized using their distinctive color, texture, and region feature. The vehicles' trajectories are than estimated using a Kalman filter, and a tracking-based detection technique is realized.

(Vaquero et al., 2017) Present full vehicle detection and tracking system that works with 3D lidar information only. They use a Convolutional Neural Network (CNN) that receives as input 3D information provided by a Velodyne HDL-64 sensor and returns a per-point classification of whether it belongs to a vehicle or not. For a multi-object tracking they used Extended Kalman Filters (MH-EKF) that estimate the position and velocity of the surrounding vehicles.

In (Xiang et al., 2017) the moving-object detector can handle the following two situations: static background and moving background. For static background, a pixel-level video foreground detector is given to detect vehicles, which can update background model continuously. For moving background, image-registration is employed to estimate the camera motion. Finally, a multi-object management module can efficiently analyze and validate the status of the tracked vehicles with multi-threading technique.

Other study (Xu et al., 2016) based on a hybrid vehicle detection scheme which integrates the Viola-Jones (V-J) and linear SVM classifier with HOG feature (HOG + SVM) methods is proposed for vehicle detection from low-altitude unmanned aerial vehicle (UAV) images.

In this paper we introduce a system of detection and tracking vehicles (mainly cars) for the prevention of road and highway accidents. At first we detect key objects (cars), for this we used Oriented Gradient Histogram (HOG) and Large Margin Separators (SVM). The choice of these two methods is due on the one hand to the efficiency and performance of HOG as an appearance descriptor (Yang et al., 2018) and SVMs (Chauhan et al, 2019) (Zgarni & Braham, 2018) as a classifier and on the other hand to the proven robustness of the combination of these two methods in various applications of computer vision (THU et al., 2018) (Bakheet, 2017) (Kaur & Sangeeta, 2016). Then a motion model based on adaptive kalman filter (Rana et al., 2020) (Katzfuss et al., 2016) is established to tracking previously detected vehicles and estimate the trajectory of vehicles. This allow us to detect the vehicles in violation and therefore to prevent road accidents.

The detection system that we have implemented is applied to scenes of road sections filmed by us in the wilaya of Guelma (located in the east of Algeria).

The tests carried out on several videos of road scenes have given satisfactory results but can be improved and exploited for the realization of a system of detection and monitoring of all types of vehicles in road and motorway scenes and therefore to participate in the construction of intelligent road traffic control systems applied on Algerian roads.

The remainder of this paper is structured as follows. In Section 2 we introduce the proposed system architecture where the principal steps are developed. In Section 3, the framework for the whole system and the experiment results are introduced. Finally, in Section 4, we provide conclusions and discuss future research directions.

2. Method

The proposed system consists of two modules (1) detection module (2) tracking and trajectory estimation module. Figure 1 describes the main parts of system architecture.

2.1 Vehicle Detection

2.1.1 Detection of moving objects

The detection of moving objects is done by background subtraction (Fig.2). The principle is the comparison between two images, the current image and the background image. The subtraction of these images makes it possible to generate the moving pixels; these pixels are grouped into labeled regions. Each region is represented by the position and size of its bounding box associated with the region.

Thus, the calculation of the difference image is the difference between the current image and the background image provided that the result is greater than the threshold:

The difference image = (the current image - the background image)> threshold.

(a) (b)

Figure 2: Detection of moving objects (Boukemoum, 2019)

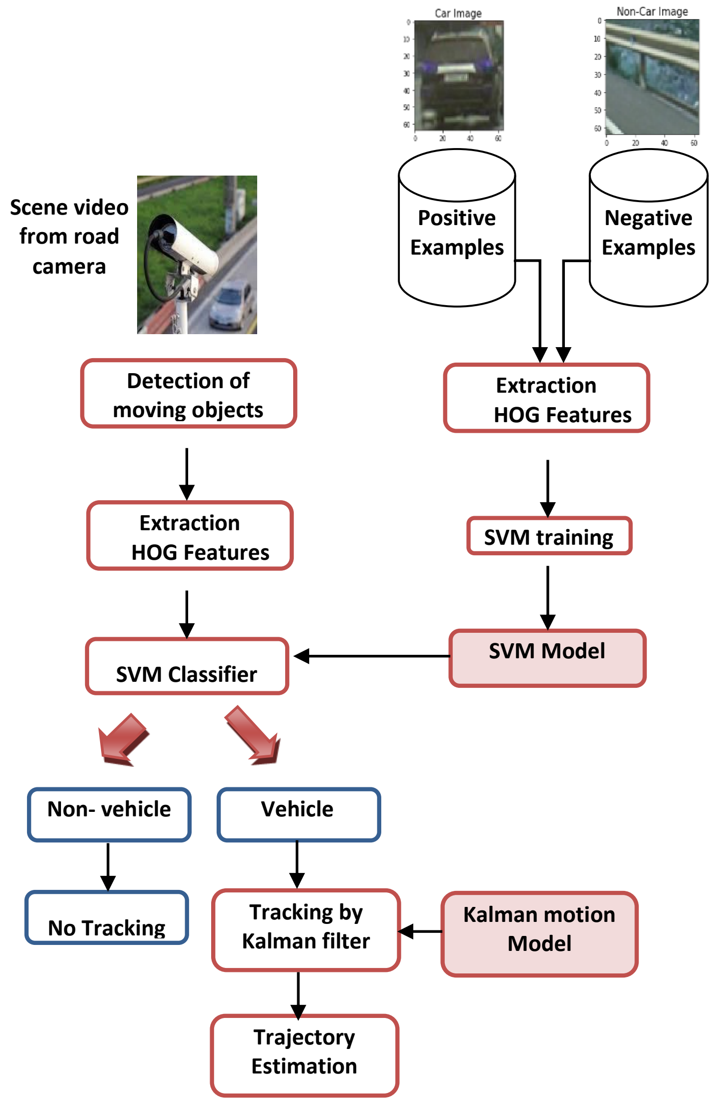


Figure.1: Proposed system architecture

2.1.2 HOG feature extraction

After having detected the moving objects in the scene, the next step is to extract their HOG features, the main steps are illustrated as follow (Boukemoum, 2019):

1. Reducing the size of detected object to have patches 128x64 pixels.
2. Calculation of horizontal and vertical gradients by Sobel filter whose kernel given by Eq. 1 and Eq. 2 as follow:

$$D_x = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} \quad (1)$$

$$D_y = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \quad (2)$$

3. Calculation of amplitude and orientation:

$$g = \sqrt{dx^2 + dy^2} \tag{3}$$

$$O = \tan^{-1}\frac{dy}{dx} \tag{4}$$

4. Histogram calculation: For each box of the block, we make the projection on the histogram table to classify the amplitude in the interval of the histogram tables (Fig.2).

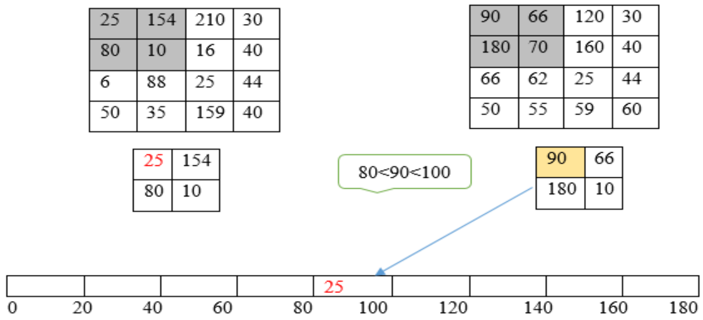


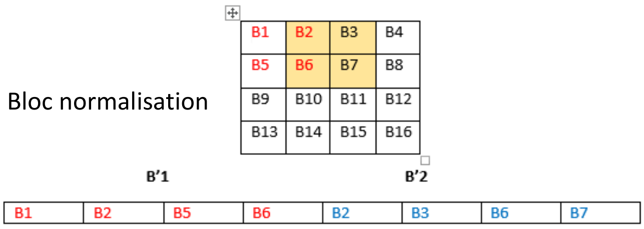
Figure .2 : Histogramme calculation

5. Block normalization: Spatial accumulation groups the contiguous cell rows of cells into blocks (Fig.3).

   The descriptor of each block is then independently normalized to have a constant norm by the division of each histogram class in the block.

   The blocks are generally overlapped by one or more cells so that each cell is represented several times in the final descriptor formed by the concatenation of all the blocks.

Figure 3 : Bloc normalisation



2.1.3 Vehicle/non vehicle classification

In order to recognize vehicles, it is necessary to build a classification model. In this case, we used Wide Margin Separators (SVM) (Chauhan et al, 2019) (Zgarni & Braham, 2018) (Boukemoum, 2019).

The following steps the following steps summarize the phases of learning and construction of the classification model:

1. Input a training set: $S = \{(x_1, y_1), (x_N, y_N)\}$
2. Choose a Kernel: $K(.\,,.)$

3. Training a SVM in the feature space

   i.e.To find the decision function

$$f(x) = \sum \alpha_i y_i \, k(x_i, x) \qquad (5)$$

4. Classify any new object and to test efficiency on the research of data.

There is usually no automatic way to choose a Kernel and to adjust the corresponding parameters, therefore we usually have to try different Kernels and parameters. In our case we we have performed tests on several kernels but the best results are obtained with the RBF (Radial Basis Function) kernel given by (Eq. 6):

$$K(x, x') = e^{-\frac{||xi-xj||^2}{2\sigma^2}} \qquad (6)$$

The parameter σ allows adjusting the width of the Gaussian. Taking a large σ, the similarity of one example to those around it will be quite high, while taking an σ tending to 0, the example will not be similar to any other.

2.2 Vehicle tracking

Video-based target tracking predicts the existence of the target, location, size, velocity, and other information of target vehicles from previous frames. Kalman filtering is an efficient way to address target tracking

2.2.1 Kalman filter tracking

The Kalman filter is described by dynamic and observation equations, which facilitate prediction and automatic correction.

The current state is predicted according to the characteristic of the moving object in the previous state regardless of the specific motion of the target. The next state of the moving object is then predicted. Computing the state transition equation of the Kalman filter requires accurate data to correct the estimated value of parameters (Fig. 4).

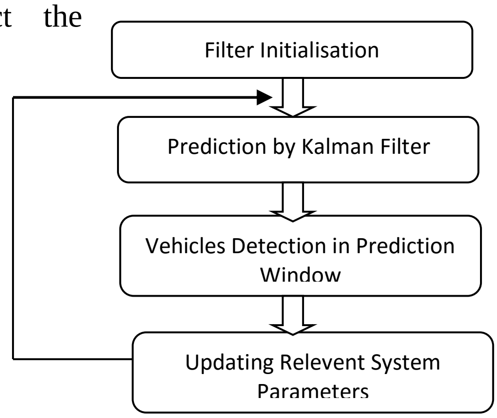
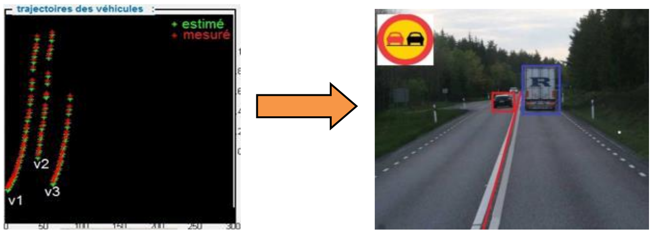


Figure 4 : Kalman filter tracking

2.2.2 Trajectory vehicle estimation

The main objective of the estimation of the trajectory is to detect the vehicles in violation mainly those which cross the continuous line (Fig. 5).

A representation of the trajectories of the followed vehicles is done in real time with the progress of the video; the representation is made according to Cartesian coordinates on the y direction only (Belhadad & Menai, 2017)



Trajectory estimation   Detection vehicle in violation

Figure 5 : Trajectory vehicle estimation

3 Results and Discussions

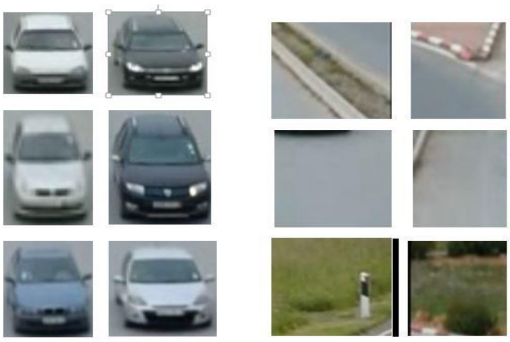
3.1 Dataset

The training dataset (Fig.6) used is composed of vehicle patch (positive examples) and non-vehicles patch (negative examples) extracted from video filmed in our country highways and roads.

The database of the positive examples contains cars of different brands, colors and sizes filmed from the front and back.

The database of the negative examples contains all that may exist in the scene filmed except cars for example: tar (road), tree, sidewalk, road signs, etc…

Our final tests are performed on video filmed in road and highway in Guelma city (situated in the east of Algeria).



(a)   (b)

Figure 6: Example of training dataset. (a) Positive examples (b) Negative examples

3.2 SVM training

SVM training results are evaluated by the following parameters: TP, FP, TN, FN described by the following table (Tab.1)

Where:

P = Positive; N = Negative;

TP = True Positive; FP = False Positive;

TN = True Negative; FN = False Negative.

		Actual Class	
		P	N
Predicted Class	P	TP	FP
	N	FN	TN

Table 1 : SVM learning assessment

We evaluated the training of the SVM on two dataset: the training dataset and a dataset of new samples never presented to the classifier, which we called the test dataset. The obtained results are described in Tab. 2 and Tab. 3.

Where:

$$TPR = \frac{TP}{TP + FN} \qquad (7)$$

$$FPR = 1 - TPR \qquad (8)$$

$$TNR = \frac{TN}{TN + FP} \qquad (9)$$

$$FNR = 1 - TNR \qquad (10)$$

Training Rate	**Percentage**
TPR	94.44%
FPR	5.56%
TNR	87%
FNR	13%

Table 2 : SVM training rates

Testing rate	**Percentage**
TPR	84%
FPR	16%
TNR	79%
FNR	21%

Table 3 : SVM testing rates

Regarding to the obtained training (Tab.2) and testing rate (Tab.3) considered sufficiently high to decide whether the moving object belongs to the vehicle class or not we can therefore adopt SVM model for the vehicle / non-vehicle classification.

The positive classification (vehicle) of the detected moving object will be followed by the extraction of the size and the center of gravity of the blob (Belhadad & Menai, 2017) .

The coordinates of the center of gravity will serve as a starting point for the kalman tracking process. Fig. 7 illustrate some tracking result on several video scenes.

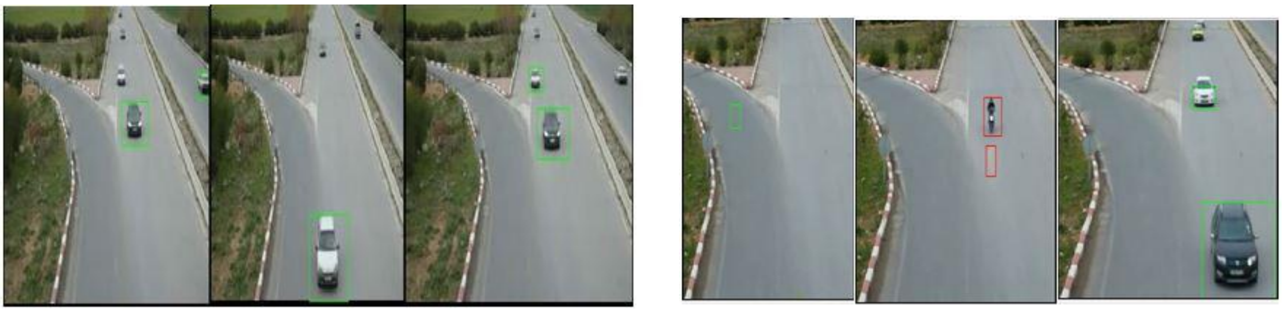


Figure 7: Example of vehicle detection and tracking

4 Conclusion

In this framework we propose a vehicle detection, classification and tracking system mainly cars based on the use of a strong classifier (SVM) trained on the relevant characteristics of HOG and robust motion predictor insensitive to disturbance which is kalman filter. The satisfactory results obtained are still considered preliminary because we will validate them on several video scenes of Algerian roads and highways before comparing them with existing road and highway prevention assistance systems used in other countries.

Acknowledgment

Author would like to thank the LAIG laboratory and “8 Mai 1945” University of Guelma for supporting this project.

References

[1] A. P. Shukla, Mona Saini “Moving Object Tracking of Vehicle Detection”: A Concise Review, International Journal of Signal Processing, Image Processing and Pattern Recognition Vol.8, No.3 2015, pp.169-176 http://dx.doi.org/10.14257/ijsip.2015.8.3.15.

[2] X. Wang, L. Xu, H. Sun, J. Xin and N. Zheng, "On-Road Vehicle Detection and Tracking Using MMW Radar and Monovision Fusion,"in IEEE Transactions on Intelligent Transportation Systems, vol. 17, no. 7, pp. 2075-2084, July 2016, doi: 10.1109/TITS.2016.2533542.

[3] B. Tian, Y. Li, B. Li and D. Wen, "Rear-View Vehicle Detection and Tracking by Combining Multiple Parts for Complex Urban Surveillance," in IEEE Transactions on Intelligent Transportation Systems, vol. 15, no. 2, pp. 597-606, April 2014, doi: 10.1109/TITS.2013.2283302.

[4] V. Vaquero, I. del Pino, F. Moreno-Noguer, J. Solà, A. Sanfeliu and J. Andrade-Cetto, "Deconvolutional networks for point-cloud vehicle detection and tracking in driving scenarios," 2017 European Conference on Mobile Robots (ECMR), Paris, 2017, pp. 1-7, doi: 10.1109/ECMR.2017.8098657.

[5] Xiang, X.; Zhai, M.; Lv, N.; El Saddik, “A. Vehicle Counting Based on Vehicle Detection and Tracking from Aerial Videos”. Sensors 2018, 18, 2560.

[6] Yongzheng Xu & all. “A Hybrid Vehicle Detection Method Based on Viola-Jones and HOG + SVM from UAV Images”, Sensors 2016, 16, 1325; doi:10.3390/s16081325.

[7] Zi Yang, Lilian S.C. Pun-Cheng, “Vehicle detection in intelligent transportation systems and its applications under varying environments: A review”,Image and Vision Computing, Volume 69,v2018, Pages 143-154, ISSN 0262-8856, https://doi.org/10.1016/j.imavis.2017.09.008.

[8] V. K. Chauhan et al, “Problem formulations and solvers in linear SVM: areview”, Springer Science+Business Media B.V., part of Springer Nature (2019) 52:803–855 https://doi.org/10.1007/s10462-018-9614-6.

[9]Zgarni, S., & Braham, A. (2018, March). Classification of Bearing Fault Detection Using Multiclass SVM: A Comparative Study. In 2018 15th International Multi-Conference on Systems, Signals & Devices (SSD) (pp. 888-892). IEEE.

[10] THU, M., Suvonvorn, N., Karnjanadecha, M. (2018) Pedestrian Detection using Linear SVM Classifier with HOG.

[11] Bakheet, S. (2017). An SVM framework for malignant melanoma detection based on optimized HOG features. Computation, 5(1), 4.

[12] M. Kaur, M. Sangeeta (2016) Review on Signature Recognition using Neural Network, SVM, Classifier Combination of HOG and LBP Features.

[13] Rana, M. M., Halim, N., Rahamna, M. M., & Abdelhadi, A. (2020, February). Position and Velocity Estimations of 2D-Moving Object Using Kalman Filter: Literature Review. In 2020 22nd International Conference on Advanced Communication Technology (ICACT) (pp. 541-544). IEEE.

[14] Katzfuss, M., Stroud, J. R., & Wikle, C. K. (2016). Understanding the ensemble Kalman filter. The American Statistician, 70(4), 350-357.

[15] Boukemoum Z. (2019). “Détection des véhicules par Histogramme Orienté Gradient”, Master degree, Computer science, 8 Mai 1945 University, Guelma, Algeria.

[16] S. Belhadad, M. Menai, (2017). “Detection et suivi de véhicules en trafic routier et Autoroutier”, Master degree, Computer science, 8 Mai 1945 University, Guelma, Algeria.