DOI: 10.2352/ISSN.2470-1173.2016.3.VSTIA-515

Vehicle type recognition using multiple-feature combinations

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Abstract

This paper proposes a real-time vehicle tracking and type recognition system. An object tracker is recruited to detect vehicles within CCTV video footage. Subsequently, the vehicle region-of-interest within each frame are analysed using a set of features that consists of Region Features, Histogram of Oriented Gradient (HOG) and Local Binary Pattern (LBP) histogram features. Finally, a Support Vector Machine (SVM) is recruited as the classification tool to categorize vehicles into two classes: cars and vans. The proposed technique was tested on a dataset of 60 vehicles comprising of a mix of frontal/rear and angular views. Experimental results prove that the proposed technique offers a very high level of accuracy thereby promising applicability in real-life situations.

Keywords: Vehicle Type Recognition; HOG; LBP histogram; region descriptors; SVM.

Introduction

In recent years, vehicle recognition systems have become extremely beneficial in application domains such as traffic management, access control, toll collection and environmental air pollution estimation. In many cases, Automatic Number Plate Recognition (ANPR) has been employed to accommodate this task. Cameras are normally installed at the entry gates to capture the Number Plates (NPs) of go-through vehicles. For each of them, the corresponding license information may be extracted and mapped to the vehicle registration information database. After locating the vehicle's registration details, a parking ticket or a toll ticket could be issued. Although ANPR can provide a level of security, they can be easily compromised using a number of techniques such as number plate cloning. The inclusion of further vehicle descriptions such as its type can be expected to lead to a more secure system. For example, the addition of such a description can be used to prevent a lorry driver with a cloned number plate from using the small vehicle passage through toll gates in an attempt to pay lower charges. Vehicle Type Recognition systems can also be effectively used in environmental air pollution monitoring where the volume of emission is directly linked to the size of the vehicle, which in turn is related to vehicle type.

Vehicle detection and type recognition is an interesting research idea that has been attracting significant attention from researchers, both in the field of computer vision and artificial intelligence. Consequently, a substantial body of literature exists that propose a number of computer vision and machine learning-based methodologies that claim to detect and identify vehicles and their type. A few notable ones are discussed in the following paragraph.

Wang and Lien [1] utilized local features including roof, tail-lights and head lights to detect vehicles from frontal and rear view vehicle images. The classifier selected in this research is the maximum likelihood Bayesian decision rule. In [2], Ozkurt and Camci proposed a technique for vehicle classification using a Neural Network (NN) classifier. The classification process was performed based on region features. Daigavane et al. [3] used a frame difference technique with morphological operators such as dilation and erosion for detecting and counting vehicles. In a mid-field video surveillance framework, Ma and Grimson [4] presented an edge-based technique using modified Scale-Invariant Feature Transform (SIFT) for vehicle detection and classification. The training set consists of 50 images in each of the four classes: cars, vans, sedans and taxis. Those numbers in test set were 200 images of cars, vans and sedans plus 130 images for taxis. In a different approach [5], Kafai and Bhanu recruited a Hybrid Dynamic Bayesian Network (HDBN) to classify vehicles using rear view images. A set of eleven features are extracted including the angle between tail light and the number plate and other vehicle dimensions. HDBN was compared with three other classifiers and it was claimed by the authors as being most effective for rear view vehicle classification. Li et al. [6], on the other hand, adopted an AND-OR graph (AOG) to represent and detect vehicles based on both of frontal and rear views. Their experiments showed that the system is reliable even in congested road traffic conditions. Recently, Ambardekar et al. [5] introduced a remarkable study on vehicle classification. In this work, the authors utilised the dataset that used in [4] to examine several different approaches, including Linear Discriminant Analysis (LDA), Principle Component Analysis (PCA), Distance From Vehicle Space (DFVS), Distance In Vehicle Space (DIVS) and Constellation based methods.

It is worth noticing that although some noticeable and encouraging results have been published, there still remain two constrains that demand further attention: view dependence and frame selection.

Firstly, it is noticed that the aforementioned techniques are heavily dependent on camera angle and view-point (frontal/rear). A change of camera angle requires a change of the feature set and possibly the classification technique. In practice, a CCTV camera's orientation and angle may require a change (in order to provide a better field of view) or may change inadvertently due to routine maintenance or wind, especially when the camera is installed outdoors. Re-designing the system to work with a different set of features, classifiers and algorithms or re-applying camera calibration is typically a non-trivial and time-consuming task. The need, thus, is for a technique that performs vehicle detection and type recognition independent of the camera view angle. To address this issue, we propose to utilise a set of multiple scale and rotation invariant features.

Secondly, it can be observed from the literature summarized above, that most of the proposed systems only work with manually selected images thereby severely hampering practical implementation. As CCTV cameras are intended to record footage on

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DOI: 10.2352/ISSN.2470-1173.2016.3.VSTIA-515

a continuous basis, the system will have to process every single frame of the recorded video. To overcome this issue, a vehicular object detector or tracker could be employed in order to select the relevant frames in the video footage. Basically, a vehicle detector can determine when a vehicle appears in a frame before activating the recognition system. A vehicle tracker can also provide extra information to locate the vehicle in the frame. Consequently, in our approach, we embed a simple vehicle tracker that significantly improves the frame selection scheme.

The rest of the paper is divided as follows. Section II presents the proposed vehicle classification system. Section III describes the experimental setup and analyses the results obtained. Section IV provides a comparison between the proposed system and the other approaches that are found in the state-of-the-art for vehicle detection and type recognition. Conclusion and further work are discussed in Section V.

Proposed System

The proposed system recruits several well-studied techniques in Computer Vision area. They are: Gaussian Mixture Model (GMM) [8], Histogram of Oriented Gradients (HOG) [9], Local Binary Patterns [10] and Support Vector Machine (SVM) classification [11].

The system has four well-defined stages: (A) A tracker (B) A training/test image generator (C) A feature extractor and classificator (D) A result accummulator. As proposed in the previous section, an object tracker is recruited to support the frame selection process. The input video is passed to a tracker which identifies frames that contain vehicular objects along with other relevant information. After that, an image pre-processing stage is performed to convert the tracked frames into appropriate training/test images. Those images are subsequently sent to the principle module Vehicle Type Recognition which will extract the feature vectors and classify them. Finally, all single frame recognition results for each vehicle are accumulated and categorized according to vehicle type.

In our experiments, based on the number of vehicular samples captured from the video footage, we only focus on two key types: cars and vans.

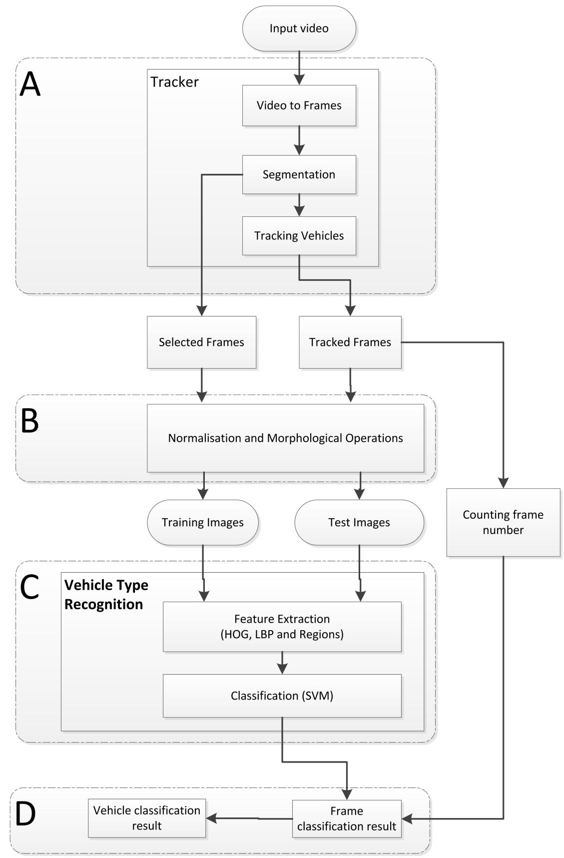

Figure 1: The proposed system

A. A tracker

The tracker's key functions are detecting and segmenting foreground objects. To this end, a GMM based background modelling algorithm as presented in [12] has been employed. A simple connected components tracking algorithm is applied to detect the foreground objects which are subsequently passed on to the type recognition module as test images.

The object tracker returns a list of objects detected from the input video, along with the frames that contains those objects. In such frames, the background is subtracted i.e. all background pixels are replaced by black pixels (value 0). In addition, each vehicular object information is presented as a single line of the form: *[Object index, frame index, bounding box information]*. The bounding box which is the smallest rectangle containing the tracked object is represented by the top-left corner coordinates and the size of the rectangle.

This information can be used to crop the bounding box of the object from the corresponding background subtracted frame. In this particular case, the bounding box of the third vehicle detected could be extracted from frame 90th by starting from the point (530, 149) and shifting 231 pixels and 211 pixels each coordination respectively. Table 1 demonstrates part of a vehicle tracked list.

Object index	Frame index	Top-left point		Bounding box size	
3	90	530	149	231	211
3	91	531	153	236	213
3	92	532	157	241	215
3	93	534	161	245	217
3	94	536	164	250	219
3	95	538	169	255	221
3	96	539	173	262	223
3	97	542	178	267	224
3	98	544	185	274	224
3	99	547	191	280	224

Table 1: A part of a vehicle tracked list

B. A training/test image generator

This stage converts the bounding box of each vehicle in each frame to appropriate training and test images. First, the Region of Interest (ROI), which is the bounding box is cropped and normalised from the three-channel colour image to a single-channel grey-scale image. Secondly, morphological operations are per-

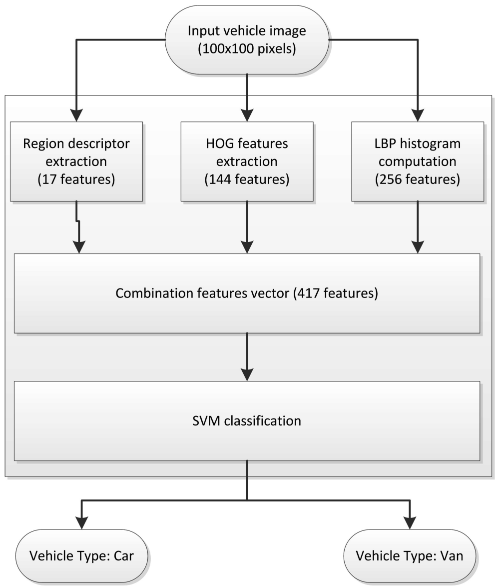

Figure 2: Vehicle Type Recognition module

formed on the normalised ROI to improve the segmented vehicle shape. This is necessary operation since from visual observation, it was noticed that the segmented frames normally contain a number of unwanted artifacts within the cropped bounding box. Therefore, different morphological operations including dilation and erosion need to be applied to remove them. Finally, the ROIs are resized into fixed size images before passing them on to the Feature Extraction and Classification stage. That step ensures that all the training and test images are of the same dimensions, thus providing the same feature vector length.

An attempt was made to find the optimum size of the training and test images in order to balance the amount of features extracted and the computational cost. It was found that in the proposed experimental set up, a dimension of 100×100 pixels offers a good tradeoff between feature set dimensionality and computational complexity.

C. A feature extractor and classificator

The system utilises a combined feature vector consisting of Region features, HOG and LBP histogram features as shown in Fig. 2. HOG, first introduced by Dalal and Triggs [9] has been widely used in both human detection [13], [14] and vehicle detection [15], [16]. On the other hand, LBP [10], is an effective way to encode the local structure around each pixel. LBP is mainly applied in human detection [17].

Literature survey reveals that a combination of HOG-LBP features has been successful in a number of human detection systems. In an outstanding research [18], Wang et al. introduced a novel HOG-LBP human detector with partial occlusion handling capability. In testing the system on the well-known INRIA dataset, the detection accuracy was nearly 98%. Many successive papers such as [19] and [20] reiterated the advantages of HOG-LBP, also affirmed SVM as the best performing classification method when considering a combined feature set. Nevertheless, HOG-LBP has not been rigorously evaluated in any vehicle detection strategy so far.

In our system, we present a novel algorithm that exploits the advantages of these two features. While HOG is exceptional in capturing the edge or local shape information, LBP is a powerful local feature for texture classification. Therefore these two features complement each other. Additionally, we enhance the features set with 13 Region descriptors to increase the accuracy. The Region descriptors considered are:

- Area [21]: The total number of pixels that are included in the ROI.
- Centroid [21]: Horizontal and vertical coordinates of the center of mass that represent the centroid.
- Bounding Box [22]: The smallest rectangle containing the ROI. Bounding box features are the top-left corner coordinates and the size of the rectangle.
- Eccentricity [22]: The ratio of the length of the maximum chord A to the maximum chord B, which is perpendicular to the ROI enclosed within the rectangle.
- Major Axis Length [22]: The length in pixels of the major axis of the ellipse that has the same second moments as the ROI.
- Minor Axis Length [22]: The length in pixels of the minor axis of the ellipse that has the same second moments as the ROI.
- Orientation [22]: The angle in degrees between the x-axis and the major axis of the ellipse that has the same second-moments as the ROI.
- Filled Area [22]: The number of pixels in the filled image - a binary image (logical) of the same size as the bounding box.
- Convex Area [22]: The number of pixels within the filled convex hull of the ROI.
- EquivDiameter [22]: The diameter of a circle having the same area as the ROI.
- Solidity [22]: The proportion of pixels in the convex hull that are also within the ROI.
- Extent [22]: The proportion of pixels in the bounding box that are also in the ROI.
- Perimeter [22]: The length in pixels of the boundary of the ROI.

Whilst horizontal and vertical coordinates of the centroid are computed as two separate centroid features, the bounding box provides the x and y co-ordinates of the start point (top left corner), the width and the height of the rectangle. In total, 17 Region features are constructed.

From each 100×100 pixel training and test image, a 256-bin LBP histogram is computed. In this particular experiment, we select the HOG cell size as [32, 32] pixels which provides 144 features. Those features are combined altogether, accumulating a feature vector of length 417.

This feature vector was fed to the SVM classifier. SVM was chosen due to its proven accuracy rate and speed of processing. After recognition, vehicle type of each test image is recorded.

D. A result accumulator

After all the test images of each vehicle are classified, a list of vehicle type for every tracked vehicular object is disclosed. This list is an extension of the tracked vehicle list that was mentioned

DOI: 10.2352/ISSN.2470-1173.2016.3.VSTIA-515

Object index	Frame index	Top-left point		Bounding box size		Type
3	90	530	149	231	211	1
3	91	531	153	236	213	1
3	92	532	157	241	215	1
3	93	534	161	245	217	1
3	94	536	164	250	219	1
3	95	538	169	255	221	2
3	96	539	173	262	223	1
3	97	542	178	267	224	1
3	98	544	185	274	224	2
3	99	547	191	280	224	1

Table 2: A part of a vehicle type list

in Section II with the addition of an extra column that reveals the vehicle type of every vehicle in each frame. Therefore, each line of the list is represented as: *[Object index, frame index, bounding box information, vehicle type]*.

As can be seen in Table 2, the first six columns are similar to Table 1 whilst the seventh column indicating the vehicle type (1 for car and 2 for van). From the list, all individual results are combined to calculate the cumulative result. Clearly, if more than 50% the total frames are correctly classified, the vehicle is recorded as a successful recognition, or a correct classification, else flagged as false recognition. The correctly classified group is subsequently divided into three subgroups based on the percentage rate of correct frames:

- Low rate: 51% to 64%.
- Medium rate: 65% to 79%.
- High rate: greater than 80%.

Experiments and Simulation Analysis

Three hours of CCTV video footage were recorded in outdoor lighting conditions. The recordings were at 720p (frame size 1280×720 pixels) with a frame rate of 24fps. For training purpose, 60 images of 12 vehicles were selected and were classified as cars and vans.

Camera settings were chosen in such a way that (i) It mimics the camera settings as those employed on the motorways in the UK and (ii) Each vehicle will be captured with both frontal/rear and side view. This ensures that the vehicles most discriminant features could be exploited. In this experimental scenario, the camera was installed at height of 40 feet (approximately 12 meters) whilst the road is a straight stretch in the upper part of the frame and curved in the lower. Fig. 3 presents a sample video footage frame whilst Fig. 4 demonstrates the camera settings in a UK motorway.

The test dataset contains 60 vehicles including 35 cars and 25 vans with a combination of frontal/rear and angular view. The approximate duration of each vehicle in the video frame is 7 seconds, thus providing about 170 frames per vehicle for testing purposes. Fig. 5 demonstrates samples of segmented vehicles that are selected as training or test images. Within the dataset of 60 vehicles, 56 vehicles are successfully recognised (true), yielding a 93% accuracy rate. Only 4 vehicles (about 7%) were incorrectly identified. The overall result is demonstrated in Table 3 while Fig. 6 indicates a sample image in which the vehicle was incorrectly identified.

Figure 3: Sample of a video frame

Figure 4: UK motorway camera settings *(dailymail.co.uk)*

Upon further examination of such cases, it was noticed that the reason was erroneous segmentation in one of the test image while the remaining three were simply misclassified. In the case of erroneous segmentation, the vehicle was incorrectly segmented as two separate objects. The reason for that could be explained by the fact that the vehicle under consideration is silver in colour and in specific illumination, its colour appears very close to the colour of the road surface. Some parts of the car was therefore, identified as the background. Those parts were subsequently re-

Figure 5: Sample of training/test image - before normalisation

DOI: 10.2352/ISSN.2470-1173.2016.3.VSTIA-515

Result		Cars		Vans		Total	
		Frontal	Rear	Frontal	Rear		
True	L	7	3	3	2	15	56
	M	5	5	6	10	26	
	H	1	10	1	3	15	
False		3	1	0	0	4	
Total		17	18	10	15	60	
		35		25			

Table 3: Overall result

moved, thus leading to incorrect vehicle detection. However, the features extracted in each object are still sufficient to perform correct recognition; hence each part was correctly recognised as a car. In the misclassification cases, two of them are due to a shadow (a commonly occurring problem during segmentation), which significantly changes the vehicle shape. The other case is due to a SUV, which cannot be clearly discriminated as a car or a van. Further investigation into the lowest rate in successful recognition cases also reveals that a majority of misclassification errors were caused due to similar reasons i.e. indistinct shapes and shadow interference.

In observing successful classification results when considering frontal and rear view, it was observed that a majority of vehicles have fallen into medium classification rate, with nearly 50% each in both front and rear views. However, the rear view of vehicles provide a significant higher accuracy rate as compared to frontal views. Under the High Rate column, 13 rear view vehicles were recorded compared to only 2 frontal view vehicles. In contrast, under the Low Rate column, successful detection figures for the front and rear views were 5 and 10 respectively. Different successful rates for the front and rear view are depicted in detail in Fig. 7.

The deterioration in frontal view accuracy rate is predictable. When only a lower part of a vehicle is visible in the camera view, it is onerous to decide whether it is a car or a van. Therefore, the classification failed in such frames and is usually the case with most vehicle detection and recognition systems presented in literature.

Comparison with the state of the art

In this section we present the comparison between the proposed system and the other approaches that are found in the state

Figure 6: False in classification

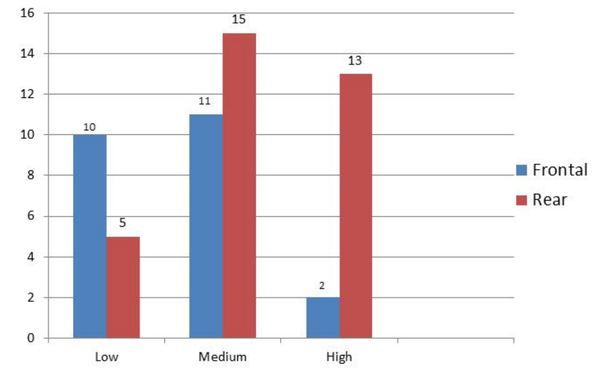

Figure 7: Successful classification in frontal and rear view

of the art.

Initially, our system achieved 93% of accuracy rate in classification, which could be considered as a satisfactory outcome. It is worth to noticing that since this is an early stage of development, our focus was on the two most common vehicle classes: cars and vans. Comparing our results in these vehicle categories with those reported in [2] and [3], our approach returned better type classification since the mentioned systems can only categorized vehicles by size (small, medium and large vehicles).

The most notable contribution of the proposed technique is the classification process, which is not restricted to fixed view angle cameras. Powered by a combination of local features that are scale and rotation invariant, our system can theoretically detect vehicles and their types in video footage captured from a wide range of angles. This makes the proposed technique quite suitable to be applied in real-world scenarios where the viewing angles of traffic surveillance cameras usually change. Regarding the camera angle and view-point, a closer look at the other techniques reveals a number of restrictions. For example, the algorithm in [5] is based on features extracted from rear view images of vehicles. Moreover, specific details such as NP and tail-lights must be visible in the image. Similar drawbacks could also be found within the data collected in in [4] and in the successive experiments of Ambardekar et al. [7]. Despite reporting an almost perfect result in one experiment (with the PCA-DIVS based algorithm), Ambardekar et al. [7] admitted that their experiments were performed under a number of constraints such as, the input video must be captured from an overlooking camera; orientation, angles and road-camera distance must be pre-measured. These points clearly indicate that the technique proposed within this paper is most suitable to be directly implemented in a real-life scenario.

Finally, in this paper we present the idea of embedding a tracker within the classification system. This significantly improves the frame selection scheme, thus conserving memory.

The comparison between different approaches and the proposed approach is presented in Table 4.

Conclusion

In this paper, a real time vehicle tracking and type recognition that is independent of camera views has been proposed. The system works on a frame selection basis utilising an object tracker. Objects detected in video frames are categorised to pro-

Approach	Key techniques	Input	Output	Limitations
[1]	Local shape features; PCA; Bayesian rules	Image	N/A	Only detection, no classification; Fixed angle view (frontal/rear view only); Specific details must be visible (roof, headlights, tail-lights).
[2]	Region features; NN	Video	Small, medium, large size vehicles	Fixed angle view (Top view only); Manually cropped video frames.
[3]	Edge, corner features; NN	Image	Small, medium, large size vehicles	Manually processed images.
[4]	Edge points; modified SIFT	Video	Cars – vans; Sedans – vans – taxis	Fixed angle view (overlooking camera only); Angle and distant must be measured; Specific details must be visible.
[5]	HDBN	Image	Sedan – Pickup – SUV/minivan	Fixed angle view (Rear view only); Specific details must be visible (LP, taillights).
[6]	AOG	Video	N/A	Only detection, no classification. Fixed angle view (frontal/rear view only); *Many assumptions and time consuming* [6].
[7]	PCA–DIVS; PCA–DIFS; PCA–SVM; LDA; Constellation model	Video	Cars – vans; Sedans – vans – taxis	Fixed angle view (overlooking camera only); Angle and distant must be measured; Specific details must be visible.
Our approach	Region features – LBP – HOG; SVM	Video	Cars – vans	Only 2 vehicle classes; Only in daytime lighting conditions.

Table 4: Comparison with the state of the art

duce the vehicle test images. A combination of features including Region descriptor, HOG and LBP histogram are extracted whilst SVM is employed as the classifier. An accuracy rate of 93% was achieved on a video of 60 vehicles both from frontal/rear and angular views. The video contains two most commonly occurring vehicle classes: cars and vans - that were captured in common outdoor lighting conditions.

Currently, we are working on several different tasks in order to improve the system. First, the dataset needs to be enlarged, not only in the training and test data size but also to include other vehicles classes such as buses and trucks. Secondly, a more intelligent tracker which can distinguish between vehicles and pedestrians will need to be employed. Third, since all the current tracked frames are treated equally, the image-weighting algorithm will also be upgraded so that only the most informative frames will need be processed thereby lowering computational complexity. Finally, video footages captured in different settings and lighting conditions will also need to be explored.

References

[1] Wang, Chi-Chen Raxle, and Jenn-Jier James Lien. "Automatic vehicle detection using local featuresA statistical approach." Intelligent Transportation Systems, IEEE Transactions on 9.1 (2008): 83-96.

[2] C. Ozkurt and F. Camci, Automatic traffic density estimation and vehicle classification for traffic surveillance systems using neural networks, Math. Comput. Appl., vol. 14, no. 3, p. 187, 2009.

[3] Daigavane, P. M., Preeti R. Bajaj, and M. B. Daigavane. "Vehicle detection and neural network application for vehicle classification." Computational Intelligence and Communication Networks (CICN), 2011 International Conference on. IEEE, 2011.

[4] Ma, Xiaoxu, and W. Eric L. Grimson. "Edge-based rich representation for vehicle classification." Computer Vision, 2005. ICCV 2005. Tenth IEEE International Conference on. Vol. 2. IEEE, 2005.

[5] M. Kafai and B. Bhanu, Dynamic Bayesian networks for vehicle classification in video, Ind. Informatics, IEEE Trans., vol. 8, no. 1, pp. 100109, 2012.

[6] Y. Li, B. Li, B. Tian, and Q. Yao, Vehicle detection based on the ANDOR graph for congested traffic conditions, Intell. Transp. Syst. IEEE Trans., vol. 14, no. 2, pp. 984993, 2013.

[7] Ambardekar, A., Nicolescu, M., Bebis, G. and Nicolescu, M. (2014). Vehicle classification framework: a comparative study. EURASIP Journal on Image and Video Processing, 2014(1), 1-13.

[8] C. Stauffer and W. E. L. Grimson, Adaptive background mixture models for real-time tracking, Proc. 1999 IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit. Cat No PR00149, vol. 2, no. c, pp. 246252, 1999.

[9] N. Dalal and B. Triggs, Histograms of oriented gradients for human detection, Proc. - 2005 IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognition, CVPR 2005, vol. I, pp. 886893, 2005.

[10] T. Ojala, M. Pietikainen, and D. Harwood, Performance evaluation of texture measures with classification based on Kullback discrimination of distributions, Proc. 12th Int. Conf. Pattern Recognit., vol. 1, pp. 582585, 1994.

[11] F. Lauer and Y. Guermeur, MSVMpack: a multi-class support vector machine package, J. Mach. Learn. Res., vol. 12, pp. 22932296, 2011.

[12] P. Kaewtrakulpong and R. Bowden, An Improved Adaptive Back-

DOI: 10.2352/ISSN.2470-1173.2016.3.VSTIA-515

ground Mixture Model for Real- time Tracking with Shadow Detection, Adv. Video Based Surveill. Syst., pp. 15, 2001.

[13] N. Dalal, B. Triggs, and C. Schmid, Human detection using oriented histograms of flow and appearance, Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics), vol. 3952 LNCS, pp. 428441, 2006.

[14] Q. Zhu, M.-C. Yeh, K.-T. Cheng, and S. Avidan, Fast Human Detection Using a Cascade of Histograms of Oriented Gradients, Comput. Vis. Pattern Recognition, 2006 IEEE Comput. Soc. Conf., vol. 2, pp. 14911498, 2006.

[15] L. Prevost, P. Negri, X. Clady, and S. M. Hanif, A cascade of boosted generative and discriminative classifiers for vehicle detection, EURASIP J. Adv. Signal Process., vol. 2008, 2008.

[16] A. Kembhavi, D. Harwood, and L. S. Davis, Vehicle detection using partial least squares, IEEE Trans. Pattern Anal. Mach. Intell., vol. 33, no. 6, pp. 12501265, 2011.

[17] Y. M. Y. Mu, S. Y. S. Yan, Y. L. Y. Liu, T. Huang, and B. Z. B. Zhou, Discriminative local binary patterns for human detection in personal album, 2008 IEEE Conf. Comput. Vis. Pattern Recognit., 2008.

[18] X. Wang, T. X. Han, and S. Yan, An HOG-LBP human detector with partial occlusion handling, Comput. Vision, 2009 IEEE 12th Int. Conf., no. Iccv, pp. 3239, 2009.

[19] P. Geismann and A. Knoll, Speeding up HOG and LBP features for pedestrian detection by multiresolution techniques, Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics), vol. 6453 LNCS, no. PART 1, pp. 243252, 2010.

[20] Y. Ma, X. Chen, and G. Chen, Pedestrian detection and tracking using HOG and oriented-LBP features, Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics), vol. 6985 LNCS, pp. 176184, 2011.

[21] C. Fosu, G. Hein, and B. Eissfeller, Determination of centroid of CCD star images, Int. Arch. Photogram. Remote Sens. , vol. 1, no. L, 2004.

[22] National Computation Infrastructure. Image Processing Toolbox, accessed Sep 2015. https://nf.nci.org.au/facilities/software/Matlab/toolbox/images/regionprops.html

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