# Pedestrian Detection for Autonomous Driving within Cooperative Communication System

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***Abstract*—The ability to perceive and understand surrounding road-users behaviors is crucial for self-driving vehicles to correctly plan reliable reactions. Computer vision that relies mostly on machine learning techniques enables autonomous vehicles to perform several required tasks such as pedestrian detection. Furthermore, within a fully autonomous driving environment, driverless vehicle has to communicate and share perceived data with its neighboring vehicles for more safe navigation. In this context, our paper proposes a warning notification diffusion solution related to real-time pedestrian presence detection, through an inter-vehicle communication system. To achieve this purpose, pedestrian and vehicle recognition is required. Thus, we implemented intended detectors. We used Histogram of Oriented Gradients (HOG) descriptor with the linear Support Vector Machine (SVM) classifier for the pedestrian detector, and Haar feature-based cascade classifier to reach vehicle detection. The performance evaluation of our solution leads to fairly good detection accuracy around 90% for pedestrian and 88% for vehicle.**

***Keywords*—HOG, SVM, Haar, Cascade, Pedestrian detection, Vehicle detection, Autonomous driving, In-Car Gateway.***

## I. Introduction

Autonomous driving [1] represents the key incoming generation of connected vehicles technologies in Internet Of Vehicles (IoV) [2]. The ability to perceive and understand the surrounding environment is crucial for self-driving vehicles mainly with complex environment situations and road users unpredictable behaviors, in order to identify potential threats and correctly plan reliable reactions. This perception process includes the necessity of having robust techniques. Many methods have been introduced whether based-computer vision [[3]-[22]], or other advanced technologies like Light Detection and Ranging (LIDAR) [[23]-[27]]. Computer vision that relies mostly on machine learning techniques enables autonomous vehicles to perform several required tasks such as object detection, recognition (i.e., pedestrian, car, bicycle, . . . etc., and related measurements estimation like distance and speed, as well as traffic signs comprehension, lane finding, . . . etc.

Furthermore, within a fully autonomous driving environment, driverless vehicles must cooperate with neighboring vehicles and share collected data, to build their self-awareness and hold road users safety. One of the most related talked road security canonical problems is pedestrian safety. In this context, embedded vehicular gateways can play a significant role to provide required connectivities for vehicles (e.g., Vehicle-to-Pedestrian (V2P) in our case). To the best of our knowledge, the use of these communication gateways is limited. This serves as the basic motivation for this paper.

Our contributions, can be summarized as follows: (1) We propose a warning notication diffusion solution related to pedestrian presence detection, through an inter-vehicle communication system, based on an In-Car Gateway [28]; (2) We intended detectors to allow pedestrian and vehicle recognition; (3a) We enhance the pedestrian detector by introducing the Histogram of Oriented Gradients (HOG) descriptor [29], with the linear Support Vector Machine (SVM) classier; (3b) We adapt Haar feature-based cascade (HFBC) classier [30] to achieve vehicle detection; and (4) We demonstrated that the performance evaluation of our solution coupled with above classifiers leads a fairly good detection accuracy around 90% for pedestrian, and 88% for vehicle.

The rest of this paper is organized as follows. Section II reviews object detection related works with emphasis on pedestrian detection contributions. Section III describes adopted algorithms behind the intended detectors, Section IV discusses our development tools and provides simulation results. Section VII, concludes the paper.

## II. Related Works

In the last decade, several research activities have been dedicated to the object detection and recognition fields. In 2017, a review study of people recognition contributions (mainly HOG-SVM, and HOG-Adaboost-based methods) had been presented [31]. Test results showed that SVM-HOG-based approaches have reached better accuracy results. Besides, [32] proposed an evaluation methodology for pedestrian detectors approaches and introduced a pedestrian annotated dataset for statistical analysis (i.e., scale, occlusion, and location). [33] discussed also pedestrian detection state of the art methods. It concluded that features improvement can lead to better detectors performances results. In the same field and within an autonomous driving context, authors in [34] have developed an approach to identify object detectors failures, based on temporal and stereo cues. [35] proposed a training data generation approach for object identification. Millard-Ball provided a game theory-based model that analyses pedestrians and self-driving vehicles interactions [36]. Authors in [37] have also worked in this context. An evaluation study of pedestrian receptivity toward fully driverless vehicles was introduced in [38]. Furthermore, [39] investigated Vehicle-to-Pedestrian communication model. Evaluation results reported that the pedestrian crossing behavior depends mainly on the gap size factor. [40] reviewed object detection contributions with a single camera model.

Yet, in this section, we highlight pedestrian detection task methods. Accordingly, Table I summarizes previous related works, which are mainly based on computer vision. We organized related contributions according to general context and autonomous driving context.

## III. Pedestrian and vehicle detection: Overview of integrated algorithms to our solution

To perform pedestrian and vehicle detection tasks, we leverage OpenCV library [41] that provides pre-trained object detection models based on HOG, SVM, and Haar-cascade methods. The HFBC classifier was motivated principally by face detection. However, it showed also an efficient and fast vehicle detection results [42]. The main general concepts of the four aforementioned techniques are outlined in the subsections below.

### A. HOG descriptor

The basic idea behind the Hog feature descriptor consists of calculating the local intensity gradients or contours directions for each cell of the subsampled input image. The HOG descriptor computation process concludes briefly the following steps:

- Step 1: Preprocessing
  As mentioned in Dalal and Triggs paper the HOG descriptor operates on 64*128 pixels scaled detection window. Typically, this input image size is sufficient to identify interesting human features body-parts. Besides, they have suggested gamma or color normalization as a preprocessing operation.
- Step 2: Gradient vector computing
  The input image is split into small cells as stated above. Accordingly, this step consists of calculating the image gradient for each pixel within every cell (i.e., the directional change in pixel values). The image gradient will highlight outlines and eliminate irrelevant information. After convolving the input image with discrete derivative masks, the direction and the magnitude of the gradient vector are computed. The direction is given by the following formula [14]:

  $$\theta = \arctan(\frac{G_x}{G_y}), \tag{1}$$

  Where:
  Gx: Approximation of horizontal gradient.
  Gy: Approximation of vertical gradient.
  The magnitude can be derived by using the formula below [14]:

  $$M_G = \sqrt{(G_x)^2 + (G_y)^2} \tag{2}$$
- Step 3: Orientation binning
  The third step aims to create the 8*8 pixel size' cell orientation histogram that is quantized into 9 bins (corresponding to 0-180 or 0-360 degrees, respectively for unsigned and signed gradient). In order to avoid aliasing, the votes (i.e, the gradient magnitudes) bilinear interpolation across orientations and locations was applied.
- Step 4: Block Normalization
  The normalization step is performed within a local block that contains 4 cells. The main intent behind this stage is to reduce illumination, contrast, and shadow variations. Different norms can be used to achieve this point [29].
- Step 5: HOG feature vector computing
  To obtain the final HOG feature vector, all normalized blocks cell histograms are combined into a single giant vector of length 3780 (size vector refers to 7 horizontal * 15 vertical blocks, with 4 cells for each block * 9 bins for each histogram).

### B. SVM classifier

Resulting descriptor features are mapped as an input for SVM to classify it as either person or not a person. SVM performs classification by building the best training data' separating hyper-plane that is at the maximal margin from the closest feature vectors of either class. The hyper-plane is defined formally as $\mathrm{w}^T.x + b$.

Where:

w: Weight vector.

x: Input vector.

b: Bias.

The margin can be written as the formula below [15]:

$$M = \frac{2}{||W||} \tag{3}$$

Maximize the margin refers to minimize the following function [15]:

$$\Phi(w) = \frac{1}{2}||w||^2 + C\sum_{k=1}^{p}\xi_k \tag{4}$$

Where:

C: Constant that controls the trade-off between classification errors number and the margin width.

$\xi_k \quad : Slackvariables.$

### C. Haar descriptor

The Haar feature value can be specified as the subtraction value of the sum of pixels lying inside white rectangle areas from pixels sum within black rectangle areas, at different scales. Three features types were defined and called as (i) two-rectangle feature, (ii) three-rectangle feature, and (ii) four-rectangle feature (see Fig. 1). The sum value of pixels is computed quickly using the Integral Image representation.

TABLE I: *Related works*

| Contribution | | Ref, Date | Main concept | Classifiers | Datasets, Train/Test | | Results |
|---|---|---|---|---|---|---|---|
| General context | Based HOG | [3] 2017 | Rearview camera-based backover warning system that addresses pedestrian pose variation and complex occlusion. | -TER-based | -Own Video | -Own Video | -TWA(Total Warning Accuracy): 97.3% |
| | | [4] 2016 | Hybrid heterogeneous architecture that is based on HOG computation reformulation and probabilistic filtering technique, to achieve pedestrian real-time detection. | -SVM | -INRIA | -INRIA<br>-Daimler | -TPR: 94.9%<br>-FPR: 5.5% |
| | | [5] 2015 | Algorithm that combines DWT (Discrete Wavelet Transform) technique with HOG method, to accelerate pedestrian detection process and minimize feature extraction computational complexity. | -Linear SVM | -INRIA | -INRIA | -Recognition Rate 85.12% |
| | | [6] 2015 | Object classifier test with NIR and LWIR images, for pedestrian detection. | -Linear SVM | -NTPD<br>-LSiFiR<br>-OSU | -NTPD<br>-LSiFiR<br>-OSU | -Higher classification effectiveness with low and very low-resolution images. |
| | | [7] 2013 | FPGA-based method to provide real-time detection, with high-resolution images. | -Linear SVM | -INRIA | -INRIA | -Gain performance in Windows/sec % studied methods results. |
| | Based CNN | [8] 2015 | Deep part-based pedestrian detector model that consists of (i) Part pool construction task, (ii) Part training task, and (iii) Shifting handling task, in order to handle occlusion. | -Linear SVM | -Caltech | -KITTI | -Average MR: 11.89% |
| | | [9] 2014 | Deep model for efficient pedestrian scene-specific features' learning. | -Linear SVM | -MIT<br>-CUHK | -MIT | -DR increased 10per % studied methods results. |
| | Based HOG+LSS | [10] 2015 | Algorithm that is based on descriptors features combination, in order to ameliorate pedestrian detection accuracy. | -SVM<br>-Adaboost | -INRIA | -INRIA | -Log-average MR: 25-26% |
| | Based HOG+CNN | [11] 2018 | Approach that assembles two-stream fusion convNets and DeCAF (Deep Convolutional Activation Features), to identify finely pedestrian action. | -SVM | -NTSEL<br>-NDRDB | -NTSEL<br>-NDRDB | -ACC: 91.01% |
| | | [12] 2017 | Approach that fuses weighted HOG and deep-learned features, to recognize pedestrian gender. | -Softmax | -CUHK<br>-PRID<br>-GRID<br>-MIT<br>-VIPeR | -CUHK<br>-PRID<br>-GRID<br>-MIT<br>-VIPeR | -MAP: 0.89<br>-AUC: 0.91 |
| | Based Haar-like +CamShift+EKF | [13] 2017 | Dynamic pedestrian tracking approach and smartphone-based warning framework within V2V context. | -Cascade | -INRIA<br>-MIT<br>-KITTI<br>-Owner | -INRIA<br>-MIT<br>-KITTI<br>-Owner | -Detection Rate: 89.6%<br>-False alarm rate: 19.4% |
| Autonomous Driving context | Based HOG | [14] 2012 | Algorithm that ameliorates human detection time. | -Linear SVM | -Owner | -INRIA | -Detection Rate: 86%<br>-False Detection: 17% |
| | Based CNN | [15] 2017 | Hybrid architecture for object recognition and detection. | -SVM | -Caltech pedestrian | -Caltech-101<br>-Caltech pedestrian | -ACC: $89.80 \pm 0.50$ (15 img/class)<br>-ACC: $92.80 \pm 0.5$ (30 img/class)<br>-Average MR: 30.0% |
| | | [16] 2016 | Method that performs sliding window, selective search, and LDCF algorithms, to detect pedestrians. | -Linear SVM | -Caltech | -Caltech | -Timing: 2.4 fps |
| | Based HOG+LBP | [17] 2016 | GPU-based pipeline for real-time pedestrian detection. | -SVM | -Own video | -Own video | -Best performances with Tegra X1 platform. |
| | Based SSD | [18] 2018 | Network architecture that involves an CFE (Comprehensive Feature Enhancement) model for object detection. | -None | -MSCOCO | -BDD | - MAP: 29.69 |
| | Based SSD+CP | [19] 2017 | Multi-task learning model that combines SSD (Single Shot Multi-Box Detector) and CP (Cartesian product) algorithms, to perform object detection and predict its distance. | -Owner | -kITTI | -KITTI | -MAP: 0.8405 |
| | Based CRF | [20] 2015 | Offline-Online vehicular environment perception approach (i.e., 3D map creation). | -Linear SVM | -KITTI | -KITTI | -Timing:0.22 s |
| | Based Context | [21] 2016 | Feature descriptor that is based on contextual information to represent pedestrian movement and street crossing intention. It adopts also MCHOG descriptor algorithm [22]. | -SVM | -Owner | -Owner | -ACC: 0.7210% |

Then, among the large calculated features, relevant features will be selected as classifier inputs, which refers to determine the best classification threshold (i.e., features with low error rate).

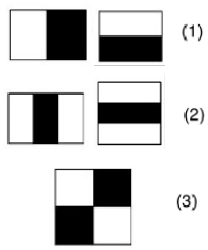


Fig. 1: **Example of rectangle feature**

### D. Cascade classifier

Cascade Classifier refers to a multistage system. It consists of diverse classifiers concatenation. After been trained, a sliding window will inspect every region and each stage (i.e., classifier) is applied to identify the object of interest within its. If an object is found, the relative region will be passed to the following stage, otherwise, its classification process is finished. The detector moves to achieve next region classification.

## IV. Implementation and simulation results

In this section, we describe briefly the overall IoV collaboration environment main components that enable us to retrieve and share useful real-time information among neighboring driverless vehicles. We highlight the broadcast of pedestrian distance related information. Then, we provide our implementation environment and simulation results.

### A. Architecture

The overview of the system architecture during the pedestrian detection stage is depicted in Fig. 2.

From the hardware point of view, self-driving vehicles are equipped with a diverse array of sensors and an embedded gateway to gather and transmit perceived data, as presented in our previous work [28]. Yet, we only use mounted cameras in our application. Here we want to describe the overall scenario: the target vehicle will capture a video stream using its front camera. Applying HOG and SVM algorithms, we check pedestrian presence. Once a pedestrian is identified, we measure his distance from the camera (based on camera angle view, object dimensions, ...etc.), so that the vehicle will be able to make more appropriate decisions (i.e., braking, steering, ...etc.). Following the same process, the target vehicle will also rely on the Haar-cascade technique to detect the rear-vehicle and calculate the distance between them, using its attached rear camera. Hence, the distance between pedestrian and rear-vehicle is determined as below:

$$D_{Pedes-RearV} = D_{Pedes-TargetV} + Vehicle_{Length}$$

+$D_{TargetV-RearV}$(5)

Through the embedded Gateway, the target vehicle will notify the related vehicle and pass the pedestrian warning information (i.e., $D_{Pedes-RearV}$).

Likewise, we assume that there is no pedestrian crossing, neighboring vehicles can obviously exchange their related distance information, as shown in Fig. 3.

### B. Hardware and Software tools

To develop our proposal, we used Python programming language [43], and OpenCV library as indicated above, which have been installed on 64 bits laptop based on Ubuntu 18.04.1 Linux operating system with Intel Core i7-3537U CPU and 8 GB of RAM. The OpenCV works with the Caltech Pedestrian dataset to reach pedestrian detection. The Caltech dataset [8] contains 640x480 30Hz video captured from a vehicle driving through regular traffic within an urban environment. Besides, we imported the required Haar-cascade classifier for our vehicle detector, which is pre-trained on the Car dataset. The car dataset was built by Brad Philip and Paul Updike and taken on the freeways of southern California and consists of 526 images at 360x240 pixels constant resolution.

The general implementation steps to detect pedestrian go as follows:

(1) Each captured video frame is converted to a grayscale video.

(2) HOG descriptor is initiated and specified (e.g., 8*8 cell size, 9 bins, gamma correction, ...etc.)

(3) Trained SVM classifier is imported for the HOG features (using "getDefaultPeopleDetector" function).

(4) "detectMultiScale" function is called to handle the pedestrian detection.

Same overall algorithm steps are applied for vehicle detection:

-Haar feature-based cascade classifier is invoked using "CascadeClassifier" function which takes as argument the intended trained classifier name.

Also, worth mentioning that python SocketServer module was called for information share phase.

### C. Simulation results

To understand detection performance we measured the accuracy average according to distance and plotted the resulting. Fig. 4 depicts the output results. The pedestrian detector performance (in blue) is evaluated on 0.5-4 meter distance range with 0.5-meter step length (from pedestrian to target vehicle). As can be seen from the figure, we obtained good accuracy rates. The average rate is around 90% (93.43%). The vehicle detector performance result (1-4 m) is illustrated in green. It achieves an average accuracy rate of about 88%. Combining both results, we can understand the total average accuracy of our proposal (in red). We notice that detection accuracy decreases slightly as pedestrian and rear-vehicle related distances are increased (i.e., distances from the target vehicle). Yet, it is clearly observed that the obtained results are good.

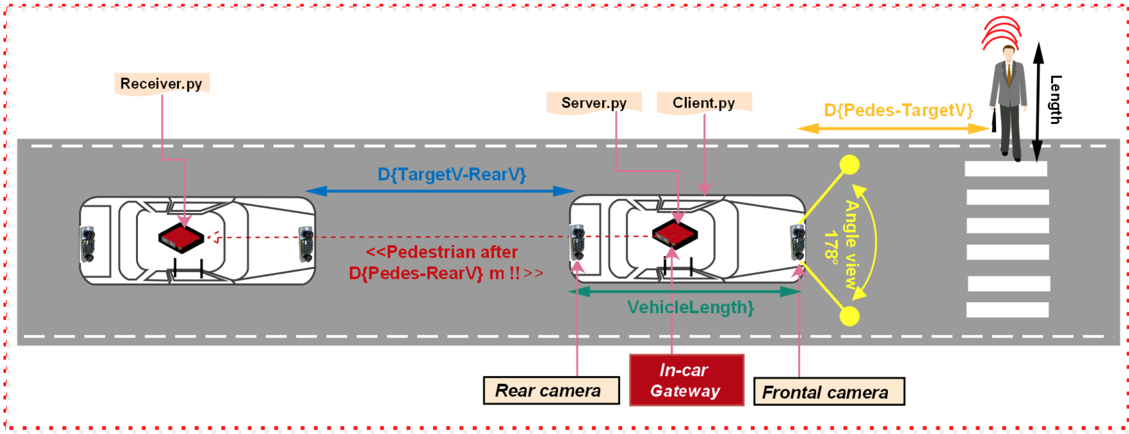


Fig. 2: **Scenario 1: Pedestrian detection environment architecture**

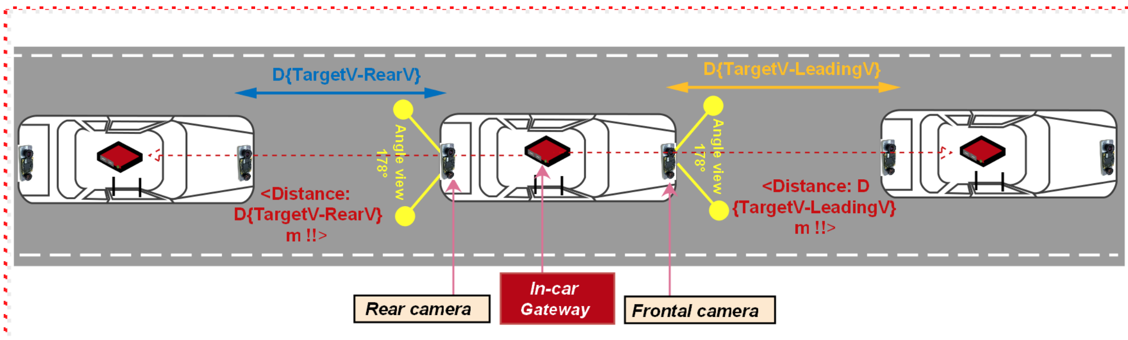


Fig. 3: **Scenario 2: Vehicle detection environment architecture**

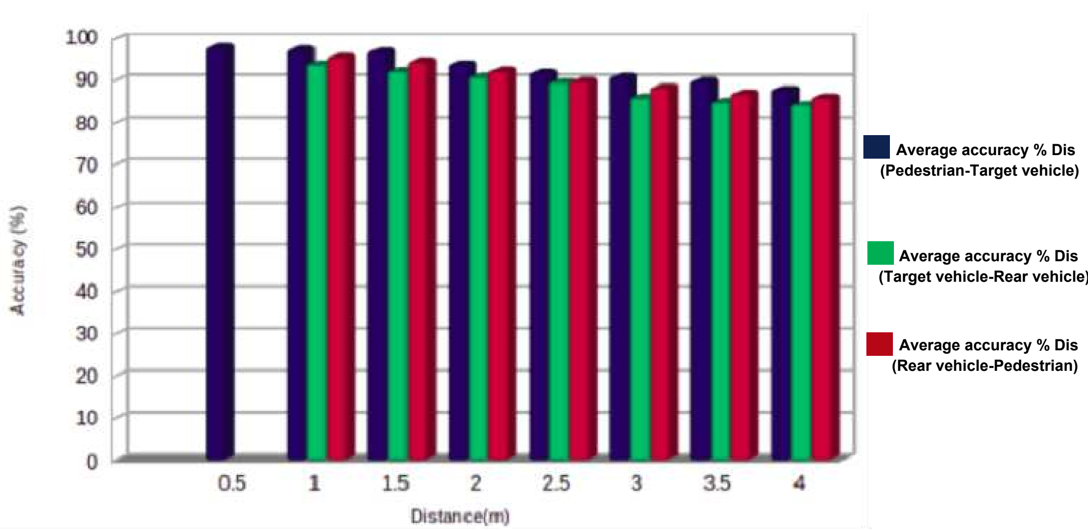


Fig. 4: Average accuracy according to the distance between **detected pedestrian and target vehicle**, **target vehicle and its rear-vehicle**, **rear-vehicle and detected pedestrian**

## V. Conclusion

In this paper, we present pedestrian presence warning notification exchange solution that is relative to autonomous driving application within the IoV collaboration system for better safe road navigation. Therefore, we have carried real-time pedestrian and vehicle detectors implementation using HOG-SVM and Haar-cascade methods. Detection information diffusion has proceeded via an inter-vehicle communication system based on mounted gateways. Simulation results showed that the intended detectors work significantly well, but performances can be more enhanced.

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## REFERENCES

[1] Sousa, N., Almeida, A., Rodrigues, J. C., and Jesus, E. N. (2017). *Dawn of autonomous vehicles: review and challenges ahead*. Proceedings of the ICE-Municipal Engineer, 1-12.

[2] Wang, J., Li, C., Li, H., and Wang, Y. (2017). *Key Technologies and Development Status of Internet of Vehicles*. In Measuring Technology and Mechatronics Automation (ICMTMA), 2017 9th International Conference on (pp. 29-32). IEEE.

[3] J. K. Suhr, and H. G. Jung. (2017). *Rearview camera-based backover warning system exploiting a combination of pose-specific pedestrian recognitions*. IEEE Transactions on Intelligent Transportation Syst.

[4] Luca Maggiani, Cedric Bourrasset, Jean-Charles Quinton, Francois Berry, and Jocelyn Serot. (2016). *Bio-inspired heterogeneous architecture for real-time pedestrian detection applications*. In Journal of Real-Time Image Processing, Springer Verlag.

[5] Hong GS, Kim BG, Hwang YS, and Kwon KK. (2015). *Fast multi-feature pedestrian detection algorithm based on histogram of oriented gradient using discrete wavelet transform*. Multimedia Tools and Applications.

[6] P. Pawlowski, K. Piniarski, and A. Dabrowski. (2015). *Pedestrian Detection in Low Resolution Night Vision Images*. Proc. of IEEE Conf. on Signal Processing -Algorithms Architectures Arrangements and Applications (SPA), pp. 185-190.

[7] M. Hahnle, F. Saxen, M. Hisung, U. Brunsmann, and K. Doll. (2013). *FPGA-based real-time pedestrian detection on high-resolution images*. In Computer Vision and Pattern Recognition Workshops (CVPRW), IEEE Conf, pp. 629-635.

[8] Y. Tian, P. Luo, X. Wang, and X. Tang. (2015). *Deep learning strong parts for pedestrian detection*. In ICCV, 1904-1912.

[9] X. Zeng, W. Ouyang, M. Wang, and X. Wang. (2014). *Deep learning of scene-specific classifier for pedestrian detection*. In ECCV, pages 472-487.

[10] Yao S, Pan S, Wang T, Zheng C, Shen W, and Chong Y. (2015). *A new pedestrian detection method based on combined HOG and LSS features*. Neurocomputing 151:1006-1014.

[11] Kataoka, H., Satoh, Y., Aoki, Y., Oikawa, S., and Matsui, Y. (2018). *Temporal and fine-grained pedestrian action recognition on driving recorder database*. Sensors, 18(2), 627.

[12] L. Cai, J. Zhu, H. Zeng, J. Chen, C. Cai, and K.K Ma. (2017). *Hog-assisted deep feature learning for pedestrian gender recognition*. Journal of the Franklin Institute.

[13] Li, F., Zhang, R., and You, F. (2017). *Fast pedestrian detection and dynamic tracking for intelligent vehicles within V2V cooperative environment*. IET Image Processing, 11(10), 833-840.

[14] Kachouane, M., Sahki, S., Lakrouf, M., and Ouadah, N. (2015). *HOG based fast human detection*. arXiv preprint arXiv:1501.02058.

[15] A. Ucar, Y. Demir, and C. Guzelis. (2017). *Object Recognition and Detection with Deep Learning for Autonomous Driving Applications*. Simulation, pp. 1-11.

[16] Tome, D., Monti, F., Baroffio, L., Bondi, L., Tagliasacchi, M., and Tubaro, S. (2016). *Deep convolutional neural networks for pedestrian detection*. Signal processing: image communication, 47, 482-489.

[17] Campmany, V., Silva, S., Espinosa, A., Moure, J. C., Vazquez, D., and Lopez, A. M. (2016). *GPU-based pedestrian detection for autonomous driving*. arXiv preprint arXiv:1611.01642.

[18] Zhao, Q., Sheng, T., Wang, Y., Ni, F., and Cai, L. (2018). *CFENet: An Accurate and Efficient Single-Shot Object Detector for Autonomous Driving*. arXiv preprint arXiv:1806.09790.

[19] Chen, Y., Zhao, D., Lv, L., and Zhang, Q. (2018). *Multi-task learning for dangerous object detection in autonomous driving*. Information Sciences, 432, 559-571.

[20] Ros, G., Ramos, S., Granados, M., Bakhtiary, A., Vazquez, D., and Lopez, A. M. (2015). *Vision-based offline-online perception paradigm for autonomous driving*. In Applications of Computer Vision (WACV), 2015 IEEE Winter Conference on (pp. 231-238). IEEE.

[21] Schneemann, F., and Heinemann, P. (2016). *Context-based detection of pedestrian crossing intention for autonomous driving in urban environments*. In Intelligent Robots and Systems (IROS), 2016 IEEE/RSJ International Conference on (pp. 2243-2248). IEEE.

[22] Koehler, S., Goldhammer, M., Bauer, S., Zecha, S., Doll, K., Brunsmann, U., and Dietmayer, K. (2013). *Stationary detection of the pedestrian's intention at intersections*. IEEE Intelligent Transportation Systems Magazine, 5(4), 87-99.

[23] Wang, H., Wang, B., Liu, B., Meng, X., and Yang, G. (2017). *Pedestrian recognition and tracking using 3D LiDAR for autonomous vehicle*. Robotics and Autonomous Systems, 88, 71-78.

[24] Lim, K. L., Drage, T., and Bra, T. (2017). *Implementation of semantic segmentation for road and lane detection on an autonomous ground vehicle with LIDAR*. In Multisensor Fusion and Integration for Intelligent Systems (MFI), 2017 IEEE International Conference on (pp. 429-434). IEEE.

[25] De Silva, V., Roche, J., and Kondoz, A. (2017). *Fusion of LiDAR and camera sensor data for environment sensing in driverless vehicles*. arXiv preprint arXiv:1710.06230.

[26] Chen, X., Ma, H., Wan, J., Li, B., and Xia, T. (2017). *Multi-view 3d object detection network for autonomous driving*. In IEEE CVPR (Vol. 1, No. 2, p. 3).

[27] Yoshioka, M., Suganuma, N., Yoneda, K., and Aldibaja, M. (2017). *Real-time object classification for autonomous vehicle using LIDAR*. In Intelligent Informatics and Biomedical Sciences (ICIIBMS), 2017 International Conference on (pp. 210-211). IEEE.

[28] Hbaieb, A., Rhaiem, O. B., and Chaari, L. (2018). *In-car Gateway Architecture for Intra and Inter-vehicular Networks*. In 2018 14th International Wireless Communications Mobile Computing Conference (IWCMC) (pp. 1489-1494). IEEE.

[29] N. Dalal and B. Triggs. (2005). *Histograms of Oriented Gradients for Human Detection*. Conference on Computer Vision and Pattern Recognition, p. 886-893, San Diego, USA.

[30] Viola, P., and Jones, M. (2001). *Rapid object detection using a boosted cascade of simple features*. In Computer Vision and Pattern Recognition, 2001. CVPR 2001. Proceedings of the 2001 IEEE Computer Society Conference on (Vol. 1, pp. I-I). IEEE.

[31] Intriago-Pazmino M, Vargas-Sandoval V, Moreno-Diaz J, Salazar-Jacome E, and Salazar-Grandes M. (2017). *Algorithms for People Recognition in Digital Images: A Systematic Review and Testing*. In World Conference on Information Systems and Technologies, pp. 436-446, Springer, Cham.

[32] R. Benenson, M. Omran, J. Hosang, and B. Schiele. (2014). *Ten years of pedestrian detection, what have we learned?*. In ECCV, CVRSUAD workshop.

[33] P. Dollar, C. Wojek, B. Schiele, and P. Perona. (2012). *Pedestrian detection: An evaluation of the state of the art*. IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, 34(4):743-761.

[34] Srinivasan Ramanagopal, M., Anderson, C., Vasudevan, R., and Johnson-Roberson, M. (2017). *Failing to Learn: Autonomously Identifying Perception Failures for Self-driving Cars*. arXiv preprint arXiv:1707.00051.

[35] Johnson-Roberson, M., Barto, C., Mehta, R., Sridhar, S. N., Rosaen, K., and Vasudevan, R. (2017). *Driving in the matrix: Can virtual worlds replace human-generated annotations for real world tasks?*. In Robotics and Automation (ICRA), 2017 IEEE International Conference on (pp. 746-753). IEEE.

[36] Millard-Ball, A. (2018). *Pedestrians, autonomous vehicles, and cities*. Journal of planning education and research, 38(1), 6-12.

[37] Rothenbucher, D., Li, J., Sirkin, D., Mok, B., and Ju, W. (2016). *Ghost driver: A field study investigating the interaction between pedestrians and driverless vehicles*. In Robot and Human Interactive Communi-

cation (RO-MAN), 2016 25th IEEE International Symposium on (pp. 795-802). IEEE.

[38] Deb, S., Strawderman, L., Carruth, D. W., DuBien, J., Smith, B., and Garrison, T. M. (2017). *Development and validation of a questionnaire to assess pedestrian receptivity toward fully autonomous vehicles*. Transportation research part C: emerging technologies, 84, 178-195.

[39] Clamann, M., Aubert, M., Cummings, and M. L. (2017). *Evaluation of vehicle-to-pedestrian communication displays for autonomous vehicles*. in Proc.Transp. Res. Board 96th Annu. Meet., Washington DC, USA.

[40] Herman, S., and Ismail, K. (2017). *Single Camera Object Detection for Self-Driving Vehicle: A Review*. Journal of the Society of Automotive Engineers Malaysia, 1(3), 198-207.

[41] https://opencv.org/.

[42] Choudhury, S., Chattopadhyay, S. P., and Hazra, T. K. (2017). *Vehicle detection and counting using haar feature-based classifier*. In Industrial Automation and Electromechanical Engineering Conference (IEMECON), 2017 8th Annual (pp. 106-109). IEEE.

[43] https://www.python.org.