International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-8 Issue-2, July 2019

Active Safety with Traffic Sign Recognition System in Vehicular Ad-Hoc Network (Vanet) using Classifier Techniques

T.Rajasekaran, Sumathi Eswaran, A.Rengarajan, T.V.Ananthan

Abstract*: Intelligent Transportation System (ITS) is one of the major research areas where the researchers focus on Vehicle traffic prediction, efficient routing algorithms, security in vehicle communication, various QoS parameters and so on..Wireless technology is progressing faster with time. People are doing research these days generally in the field of Wireless communication. VANET is the most developing exploration territory in remote correspondence. With the headway and development of the VANET, there will be an incredible upheaval in the field of telecommunication regarding quick handovers, arrange accessibility, security, wellbeing with the utilization of cutting edge applications and so on. VANET innovation is progressing with the progression of time however there are numerous issues that must be routed to make the system more overwhelming. In perspective of aforementioned, in this paper we have proposed an effective mechanism for object detection in highways using Neural Networking and proving driver assistance to enhance the existing system to the next level as Intelligent Transportation System.

Keywords* : Vehicular Ad-hoc Network (VANET), Intelligent Transportation System(ITS), LIDAR, Ultrasonic Sensor, Convolution Neural Networks(CNN), HOG and Haar Classifier.

I. INTRODUCTION

VANET: VANET has turned out to be one of the most essential research areas in the field of remote telecommunication. Before delving into the details of VANET it is important to talk about its background. VANET is a sibling of MANET which composes its correspondence framework itself with no reliance on some other frameworks. The most widely recognized use of MANET is in defense services for its effective and fundamental correspondence strategy like information sharing between different devices and so on. VANET is like MANET alongside a few adjustments. VANET includes the Portable (mobile) unit called Nodes, Road side units (RSU). Portable units are the sensors inserted in the vehicles that are called as on board units (OBU) for the processing of incoming and outgoing signals (information sharing) to and from RSUs. RSUs are fixed units that act as a portal for the communication between vehicle's OBU and the servers or to the outside world (Internet).

In general there are two kinds of communications are possible in VANET that is Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I). In the case of V2V communication the vehicles which possess Onboard Unit can communicate with other OBU enabled vehicles; such communication may include sharing of information about the current or near future traffic condition, road conditions and so on. On the other hand, the Vehicle to Infrastructure kind of communication is the communication between the vehicles's OBU and the Road Side Units, which are fixed along the road side electrical or lamp posts or in the dedicated posts. The type of information that is shared among these units may include the current traffic information forecasting to the centralized server or to the internet via RSU, which helps to broadcast the traffic information to the preceding vehicles. On the other side the information from centralized traffic servers can be received by OBU through RSU, the information such as take diversion messages, Accident alerts, road condition alerts and so on.

Artificial Intelligence:

The concepts of Artificial Intelligence, Neural networks, Deep learning and Machine Learning are really attractive. But, the actual understanding of how these technologies works is limited to very few domain experts. The below figure illustrates the hierarchy of these fascinating technologies.

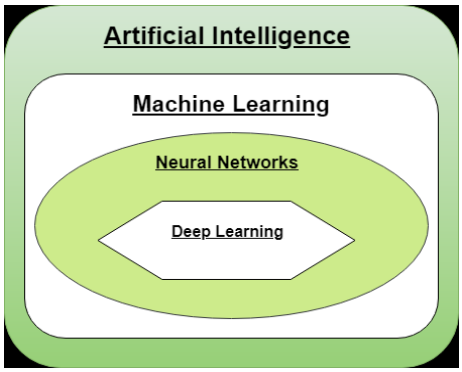


Fig.1: Artificial Intelligence Hierarchy

Revised Manuscript Received on 30 July 2019.
* Correspondence Author
T.Rajasekaran*, Research Scholar, Department of Computer Science, Dr.M.G.R. Educational and Research Institute, Chennai.
Sumathi Eswaran, Dean-Department of CSE/IT, Dr.M.G.R Educational and Research Institute, Chennai.
A.Rengarajan, Professor, Computer Science and Engineering, Vel Tech Multitech Dr.RR Dr.SR Engg. College, Chennai.
T.V.Ananthan, Professor, Department of CS, Dr.M.G.R Educational and Research Institute, Chennai.

Artificial Intelligence is the field of concentrate by which a computer (and its frameworks) build up the capacity for effectively achieving complex assignments that typically require human intelligence, for example, visual observation, decision-making, Speech recognition, Object recognition and interpretation between dialects. Artificial intelligence is typically characterized as the "investigation of influencing computers to do things that needs intelligence when handling by people", i.e., AI is concern with solving problems that are easily handled by humans but hard for computers to solve.

Machine Learning:

Machine Learning (ML) is a study that applies the standards of software engineering and measurements to make statistics models, which are utilized for future prediction and distinguishing patterns/designs in data. Machine learning is itself a kind of AI that enables programming applications to wind up progressively precise in anticipating results without being expressly coded. ML is the capacity for a Computer to yield or accomplishes something that it wasn't modified to do. While machine learning underscores on making expectations about the future, Artificial Intelligence ordinarily focuses on programming PCs to decide. In the event that you utilize an astute program that includes human-like conduct, it tends to be man-made consciousness. In any case, if the parameters are not consequently learned from information, it's not Machine Learning.

Deep Learning:

Deep Learning is one of the ways to deal with Machine Learning. Other real methodologies incorporate decision tree learning, inductive rationale programming and Bayesian systems. Deep Learning is an exceptional kind of Machine Learning. It includes the study of Artificial Neural Networks and Machine Learning related algorithms that contain more number of hidden (intermediate) layers. Deep Learning includes mathematical or scientific modeling, which can be thought of as an organization of basic blocks of a particular kind, and where a portion of these blocks can be adjusted for better prediction of resultant output.

Classification Mechanism:

Haar cascades based on Haar features of an object for detection of a traffic sign. It is a machine learning based approach where a cascade function is trained from a lot of positive and negative images. It is then used to detect objects in other images. Initially, the algorithm needs a lot of positive images (images of sign) and negative images (images without sign) to train the classifier. Then we need to extract features from it. For this, haar features shown in below image are used. They are just like our convolutional kernel. Each feature is a single value obtained by subtracting sum of pixels under white rectangle from sum of pixels under black rectangle. Now all possible sizes and locations of each kernel is used to calculate plenty of features.

According to the Government of India(GoI) statistics* released about the road accidents by our government of India, during the calendar year 2016-2017, the total number of road accidents is reported at 4,80,652 causing injuries to 4,94,624 persons and claiming 1,50,785 lives in the country. This would translate, on an average, into 1317 accidents and 413 accident deaths taking place on Indian roads every day; or 55 accidents and 17 deaths every hour. Among the vehicle categories cars, jeeps and taxis (23.6 per cent), trucks, tempos, tractors and other articulated vehicles (21.0 per cent), Buses (7.8 per cent). The National Highways constitute about 2 per cent of the total road network of India, but they accounted for 29.6 per cent of total road accidents and 34.5 per cent of total number of persons killed. The State Highways accounted for 25.3 per cent of total accidents and 27.9 per cent of the total number of persons killed in road accident in 2016-2017. From this statistical report it has been inferred that the number of accidents taken places in Highways are drastically increasing over years. On account of this, we are proposing a latest yet effective technique to reduce the accidents in highways by incorporating Artificial Intelligence, Computer vision along with Intelligent Transportation System.

* *Source- Release from the Government of India, Department of Road Transports & Highways, Transport Research Wing, New Delhi (www.morth.nic.in)*

PROPOSED WORK:

Vehicle Detection is one of the major research areas in the field of VANET, which includes various Artificial Intelligence techniques to detect as well as improve the probability of detection of the objects. The proposed work includes the following things to be done in the serial passion to accomplish the obstacle detection, traffic sign detection and recognition.

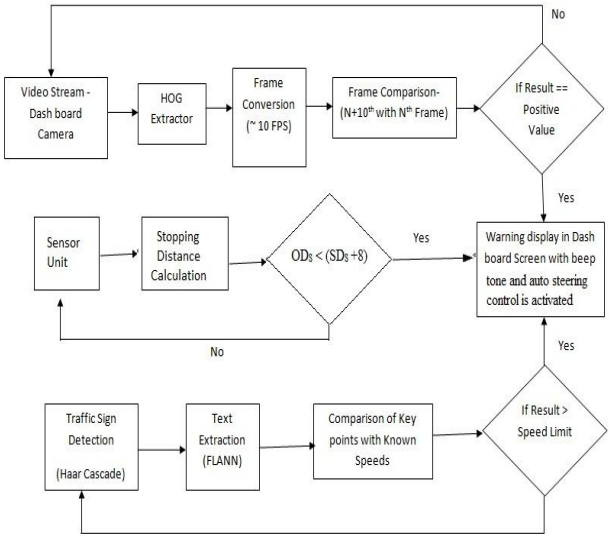


Fig.2: Overall Flow diagram of Proposed Work

Object Detection:

In the vehicle, the front cam installed near the wind shield is turned on automatically when the vehicle is ignited. It continuously captures the video and converts the captured videos in to frames, approximately 10 frames per second. The frames are compared to find the distance of the object, if anything identified in the frame. This work in the following manner, i.e. the first frame of the obtained video is compared with the 10th frame. It is obvious that if any object found in the frame 1 is increased by its dimension in the 10th frame when it is comes closer. This dimension variation is taken as a parameter to confirm that the object is getting closer to our vehicle. This comparison is done using Open Computer Vision (OpenCV) technology.

The OpenCV technology has the features of detecting objects from the real time videos, but for our work it is not necessary to have such real time detection. Since we are about to compare the 1st and 10th frames.

Fig.2: Vehicle detection with OpenCV

The OpenCV library HOG (Histogram of Oriented Gradients) extractor is used to identify the vehicles or obstacles with identification marks (Colored Square boxes). These square boxes and its dimensions are taken in to account to compare the object distances. The square box found in the 1st frame and its dimensions are calculated and store it as $OD_{N^{th}\ Frame}$ (Obtained Distance) and the same has been calculated for 10th frames and store it as $D_{N+10th\ Frame}$. Then by subtracting $N+10^{th}$ frame with N^{th} frame, we can obtain a result which is stored in OD_{Result}. If the OD_{Result} is a positive value, it is confirmed that the object is moving closer to our vehicle, then we are about to take any pre-safety measures by any means. If the result is a negative value then, we can say the objects are moving away from our vehicle so, it is not necessary to take any active safety measures.

$$OD_{Result} = OD_{N+10th\ Frame} - OD_{Nth\ Frame}$$

If,

$OD_{Result} < 0$, then the object is moving outwards.

$OD_{Result} = 0$, then the object is moving with the same speed of our vehicle.

$OD_{Result} > 0$, then the object is getting closer to our vehicle.

Stopping Distance Calculation:

This is the part where the Active Safety System for the vehicle is introduced. This phase includes LIDAR or Ultrasonic sensors to find the distance between the obstacle and our vehicle. OD_{Result}, which we have find in the previous session will confirms whether, the identified object is moving outwards or getting closer to our vehicle. But it will not give any active safety measures to avoid vehicle accidents. To include the active safety measures, we are calculating the stopping distance for our vehicle to assist the driver. We are using Ultrasonic sensor to find the distance between obstacles and our vehicle, and that distance is named as Obtained Distance (OD_S- Obtained Distance from Sensor). The results are in terms of meters. Based on the result of object comparison, the sensor module gets triggered and finds the distance between nearing object and our vehicle.

The Stopping distance (SD_S) is depends on various factors such as vehicle's velocity, weight and so on.

$$SD = V^2 / 2\mu g$$

Stopping distance (SD) in meters

v = velocity of the car (m/s)

μ = coefficient of friction (unit less)

g = acceleration due to gravity (9.80 m/s^2)

To find the coefficient of friction (μ)

$$\mu = F_k / N$$

Where,

F_K = Kinetic friction.

N = Normal force.

To find Normal force (N)

$$N = mgCos(\Theta)$$

Where,

m= mass of the object

g =acceleration due to gravity

Θ=Inclined angle

Comparison and Driver Assistance:

Once the distance value identified using sensors and the stopping distance calculated using the above formula is obtained, then it's the time to compare both the distances to decide the next event. Suppose, the obtained distance (OD_S) value is lies between SD_S + 8 meters and SD_S + 12 meters, which means there is controllable distance between the object and the vehicle. So, as a proactive measure we can alert the driver by triggering the alarm subsystem.

$$(SD_S + 8) < OD_S <= (SD_S + 12) \text{ meters}$$

The constant values, 8 and 12 are the distances in meters. Which are the suggested distances between the vehicles for the safer driving.(as suggested in the Traffic safety rules under motor vehicle act of Indian law).

Suppose, the obtained distance (OD_S) value is lesser than SD_S + 8 meters, then, the possibility for collision is high so, the Active Safety System triggered and the control is taken over by the automated emergency braking subsystem which applies the brake to prevent collision along with the warning alarm sound.

$$OD_S < (SD_S + 8) \text{ meters}$$

Traffic Sign Detection:

It is obvious that, sometimes we may unintentionally forgot to notice the traffic sign boards which may causes slight damages to even heavy accidental losses. One such thing we commonly do in our day to day life is, forget to notice the speed breaker sign, speed limit signs, men at work signs and so on, this may or may not cause that huge loss/damages, but still it is a common mistake that every one experienced at least one in their life time. So, in order to avoid such mistakes out work concentrates on analyzing the traffic signs and intimate the same over voice and even display to sign in the vehicle's dash board screen.

The traffic sign detection is done using Local Binary Patterns (LBP) or Haar Cascade classification algorithms. Unlike Convolutional Neural Networking (CNN), these algorithms don't learn by itself. i.e., these are supervised algorithms, that are need to be labeled manually and it does not support self learning. This type of algorithms have their own advantages and disadvantages i.e., it won't take time much time for self learning, since everything is labeled by the developer itself. But the results are not getting improvised every time since; self learning is not supported by these types of algorithms.

Haar-like features are attributes extracted from images used in pattern recognition. Their name comes from their similarity to Haar wavelets. The utilization of these features instead of handling gray or color level of the pixels directly. First, the pixel values inside the black area are added together; then the values in the white area are summed, as seen in below figure Then the total value of the white area is subtracted from the total value of the black area. This result is used to categorize image sub-regions.

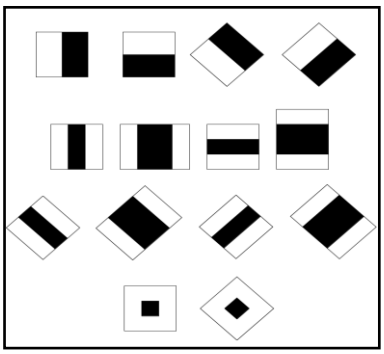


Fig. 3: Haar-like Features

Our work has time critical constraints, so it is mandatory to convey the sign details as and when a sign board is found. In this case we should least bother about increasing accuracy of the sign detection by using unsupervised CNN algorithms. In our work, LBP and Haar cascade algorithms were trained with around 2000 positive images (Images with sign boards) and 1000 negative images (images without sign boards). When compare with LBP it is preferable to go with Haar cascade algorithm, which detects the signs as quicker when compared with LBP algorithm and also support slow computational mechanisms i.e., it doesn't require high configuration systems for its computation.

Experimental Results and Analysis of Haar Classifier:

The experiment for this part use CNN algorithm and Haar-like features classifier. The recall rate (RR) are defined as follows:

$$RR = (Number\ of\ detected\ vehicles\ /\ Number\ of\ vehicles) \times 100$$

Table-1: Comparison of detected vehicles at Day time

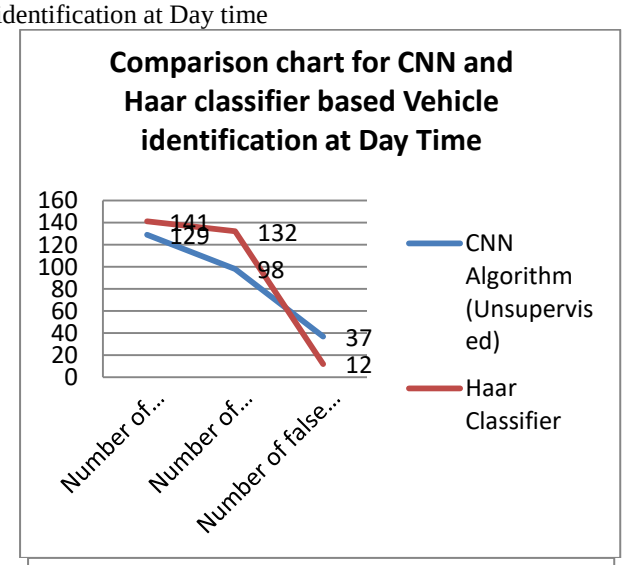
Parameters	CNN Algorithm (Unsupervised)	Haar Classifier
Number of Traffic signs	129	141
Number of Traffic signs	98	132
Number of false positives	37	12
Recall Rate (RR)	75.96%	93.61%

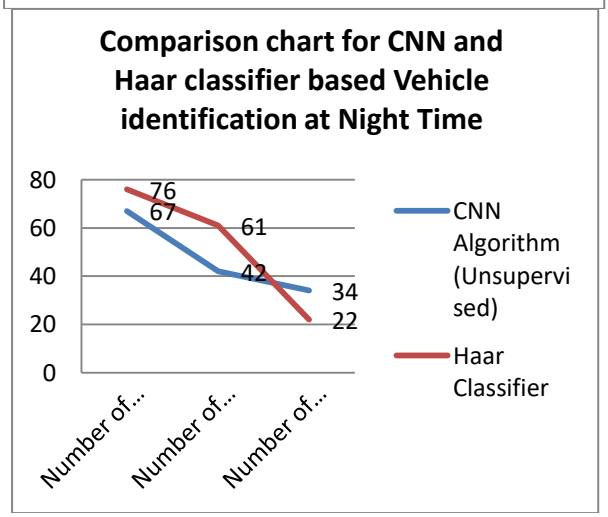
Table-2: Comparison of detected vehicles at Night time

Parameters	CNN Algorithm (Unsupervised)	Haar Classifier
Number of Traffic signs	67	76
Number of Traffic signs	42	61
Number of false positives	34	22
Recall Rate (RR)	62.68%	80.26%

Table 1 shows the detected results at day time. As we see the Recall Rate (RR) for the CNN based unsupervised algorithm are lesser than our Haar Classifier algorithm and the rate of false detection is also comparatively lesser for our approach. Table 2 shows the results at night time. Here also performance of our approach is reasonably higher than opponent algorithm By the plotted chart, it is confirmed that the traffic sign detection rate and efficiency of our approach is performing much well than the traditional approach.

Comparison chart for CNN and Haar classifier based Vehicle identification at Day time





Extraction and Warning System:

The second phase of our work concentrates on detecting texts present in the identified speed limit sign boards.

This is done using Fast Library for Approximate Nearest Neighbor (FLANN) search Library feature matching algorithm. FLANN is a library for performing fast approximate nearest neighbor searches in high dimensional spaces. It contains a collection of algorithms we found to work best for nearest neighbor search and a system for automatically choosing the best algorithm and optimum parameters depending on the given dataset.

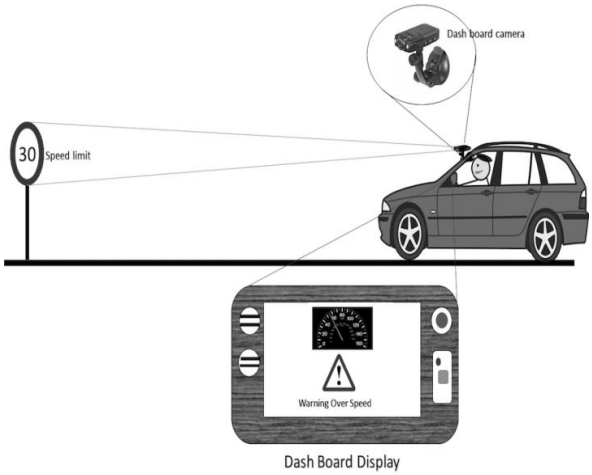


Fig.4: Speed Detection and Warning system

FLANN can contain binding for python language which we are already using it for OpenCV implementation on object detection in the first phase. After detection of texts presents in sign board is stored as a "Key points" and compare them with all known speed limits. The key point obtained is compared with the current speed limit. If it exceeds the limit, a warning signal is triggered. Warning can be a beep sound or it can be a visual signal in the vehicle's dash board screen. This will be acted as a active safety system, which alerts the driver to take necessary action towards the warning signs. Speed Assistance is done in the following manner. When a new speed limit is detected, it is added as current speed limit. After every frame, script compares current speed to current speed limit. Script runs specified command when over speeding is encountered (e.g. beep and dash board display).

II. CONCLUSION

In this paper, we proposed a novel vehicle detection and traffic sign recognition and text extraction approach for vehicle's active safety using for Haar cascading classification algorithm and FLANN library, so far Haar classifier is implemented in facial recognition purposes but in our work we incorporated Haar algorithm for detecting traffic signs. The experimental results illustrated in Table-1 and Table-2 shows that our method can significantly suppress the false positive rate and can obtain high detection accuracy that reaches more than 93%.In future work, we will focus on the research of improving the recall rate by expanding the categories and the number of traffic signs in the dataset and improving the detection performance.

REFERENCES

1. Xiang, X., Lv, N., Zhai, M., & El Saddik, A. (2017). Real-Time Parking Occupancy Detection for Gas Stations Based on Haar-AdaBoosting and CNN. IEEE Sensors Journal, 17(19), 6360–6367.doi:10.1109/jsen. 2017.2741722
2. Lee, S., Son, H., Choi, J. C., & Min, K. (2012). HOG feature extractor circuit for real-time human and vehicle detection. TENCON 2012 IEEE Region 10 Conference.doi:10.1109/tencon.2012.6412287
3. Naik, B., Nayak, J., Behera, H. S., & Abraham, A. (2014). A Harmony Search Based Gradient Descent Learning-FLANN (HS-GDL-FLANN) for Classification. Smart Innovation, Systems and Technologies, 525–539. doi:10.1007/978-81-322-2208-8_48
4. Reza Javadzadeh1, Ehsan Banihashemi, and Javad Hamidzadeh , "Fast Vehicle Detection and Counting Using Background Subtraction Technique and Prewitt Edge Detection " , International Journal of Computer Science and Telecommunications [Volume 6, Issue 10, November 2015.
5. Xiaofeng Lu, Takashi Izumi, Tomoaki Takahashi, "Moving vehicle detection based on fuzzy background subtraction" , Fuzzy Systems (FUZZ-IEEE), 2014 IEEE International Conference on 6-11 July 2014.
6. N. Dalal and B. Triggs, "Histograms of oriented gradients for human detection," in Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit., San Diego, CA, USA, 2005, pp. 886–893.
7. G. Wang, G. Ren, Z. Wu, Y. Zhao, and L. Jiang, "A hierarchical method for traffic sign classification with support vector machines," in Proc. IEEE Int. Joint Conf. Neural Netw., Dallas, TX, USA, 2013, pp. 1–6.
8. F. Zaklouta, B. Stanciulescu, and O. Hamdoun, "Traffic sign classification using K-d trees and random forests," in Proc. IEEE Int. Joint Conf. Neural Netw., San Diego, CA, USA, 2011, pp. 2151–2155.
9. J. Greenhalgh and M. Mirmehdi, "Real-time detection and recognition of road traffic signs," IEEE Trans. Intell. Transp. Syst., vol. 13, no. 4, pp. 1498–1506, Dec. 2012.
10. K. Lu, Z. Ding, and S. Ge, "Sparse-representation-based graph embedding for traffic sign recognition," IEEE Trans. Intell. Transp. Syst., vol. 13, no. 4, pp. 1515–1524, Dec. 2012.
11. Arun Varghese, G. Sreelekha, "Background subtraction for vehicle detection," Communication Technologies (GCCT), 2015 Global Conference on 23-24 April, 2015.
12. K Y. Iwasaki and H. Itoyama, "Real-time Vehicle Detection Using Information of Shadows Underneath Vehicles," in Advances in Computer, Information, and Systems Sciences, and Engineering, K. Elleithy, et al., Eds., ed: Springer Netherlands, 2006, pp. 94-98.
13. D.Y. Huang, et al., "Reliable moving vehicle detection based on the filtering of swinging tree leaves and raindrops," J. Vis. Comun. Image Represent., vol. 23, pp. 648-664, 2012.
14. Zhang K, Zhang Z, Li Z. Joint face detection and alignment using multitask cascaded convolutional networks [J], IEEE signal Processing Letters, 2016, 23(10):1499-1503.
15. Mandal B. Face recognition: Perspectives from the real world [C], IEEE 2016 14th International Conference on Control, Automation, Robotics and Vision (ICARCV), pp. 1-5, 13-15 Nov. 2016, Phuket, Thailand.
16. D. Chen, S. Ren, Y. Wei, X. Cao, and J. Sun. Joint cascade face detection and alignment. In Computer Vision–ECCV 2014. 2014.
17. M. Everingham, L. V. Gool, C. K. I. Williams, J. Winn, and A. Zisserman. The pascal visual object classes (voc) challenge, 2009.
18. P. F. Felzenszwalb, R. B. Girshick, D. McAllester, and D. Ramanan. Object detection with discriminatively trained partbased models. Pattern Analysis and Machine Intelligence, IEEE Transactions on, 2010
19. Kaehler A, Bradski G, Learning OpenCV 3 [M], O'reilly Media, Inc., 2016, Sebastopol, CA 95472, USA.
20. B. Bilgic, B.K.P. Horn, and I. Masaki, "Fast human detection with cascaded ensembles on the GPU," IEEE Intelligent Vehicles Symposium, pp. 325–332, June 2010.
21. Q. Zhu, M.C. Yeh, K.T. Cheng, and S. Avidan, "Fast Human Detection Using a Cascade of Histograms of Oriented Gradients," IEEE Conference on Computer Vision and Pattern Recognition, pp. 1491–1498, June 2006.