Comprehensive Review on Application of Vehicle Image Processing

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Abstract - *Advancement of machine learning has allowed to solve real time problem that were considered impossible using traditional programming logic .Traditionally image processing was used to monitor vehicle passively for surveillance. Development of computer vision unlocked potential to perceive surrounding environment in order to make driving more safer and comfortable. Increasing level of automation in cars is gradually reducing human involvement during driving. This literature survey discusses various application of object detection technique used in Driver safety assistance systems and vehicle surveillance .It also gives overview about autonomous vehicle and challenges and impact on society.*

KeyWords: **Autonomous vehicle, Computer vision, Deep learning, Object detection, Traffic managemen**t.

1. INTRODUCTION

Computer Vision has advanced to new level within the last ten years and is reaching human-level accuracy in many domains. Automated solution that use machine learning helps in reducing human error with added advantage of scalability at low cost.

Traditionally human-engineered feature extraction pipelines were utilised to detect objects in image. They required high knowledge of feature engineering and did not adopt to dynamic background. On the other hand Deep learning adopted semi-supervised or unsupervised learning approach that extracts underlying feature from large dataset. Advancement in deep learning especially in Deep CNN network has greatly improved precision of machine learning model. Availability of large scale dataset has played essential role in this transformation.

Great amount of information can be extracted given a vehicle image. Insurance sector can benefit from faster damage assessment and claim redressal. Traffic management can be greatly improved due to improved surveillance. Ability to detect road lane, pedestrian and animal can help in saving life. Emergence of autonomous car will make road transport safer and change experience of mobility.

Many researcher have studied application of computer vision to improve safety of vehicle.[1]-[2] discussed on safety and driver assistance technology that predominately used human-engineered feature detector such HOG and cascade based detector.[3] surveyed hand-crafted and deep learning methods for vehicle classification.[4]considered technique used for pedestrian detection.[5]-[7] studied benefits of image processing for traffic management.[8]- [9] reviewed and studied the recent trends and developments in deep learning for computer vision and integration in autonomous car.

The rest of this paper is organized as follows. In Section II, Application of computer vision in driver safety assistance are discussed. Section III discuses Application of computer vision in Vehicle surveillance, Section IV provides the overview of autonomous car. In Section V, different challenges associated with computer vision driven solution are discussed. Section VI provides concluding remark about review.

2. ADVANCED DRIVER SAFETY ASSISTANCE SYSTEMS

Advanced Driver Safety Assistance Systems are real time systems integrated with vehicle that can alert driver of imminent threat on road. They rely on input from camera, electronic and mechanical sensors. They can be categorized into comfort system and safety feature. The comfort function such as steering assist, parking assist and adaptive cruise control help in improving ride quality of driver. Safety feature such as driver drowsiness detector, pedestrian detector and Anti Lock Brake Assist can supersede driver control over car in situation that may lead to accident[11].

2.1 Driver Drowsiness Detection

Fatigued driver pose significant danger to road safety. Vehicle-based methods that monitor on sensor data such as steering wheel angle, acceleration, lateral position of car are slow for real-time intervention. Risk is associated with sensor failure that are difficult to detect. This makes image processing approach more reliable and accurate.

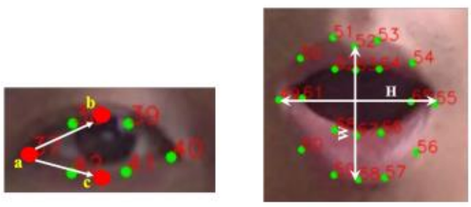

Fig -1: key facial points tracked to detect drowsiness[11]

Fatigue of driver can be detected from facial and behavioral pattern. Deng Wanghua and R. Wu [11] proposed approach where facial orientation was tracked using MC-KCF algorithm. Excessive rate of eye closure and constant yawning are associated with degree of drowsiness.A custom CNN network is built to monitoring of eye closure and mouth width-height ratio by tracking different facial points as shown in Fig 1.Illumination intensity is crucial factor should that has be taken into consideration while training process.Complexity of the real environment and diverse expression complicates solution that can generalize to environment and user[11].

2.3 Lane Detection

Self driving car needs to handle is detecting traffic lane. Lane detection was generally done using primitive geometric modelling technique that required image processing to extract pixel feature of lanes and use pixel fitting algorithm to extrapolate lane boundaries[3].

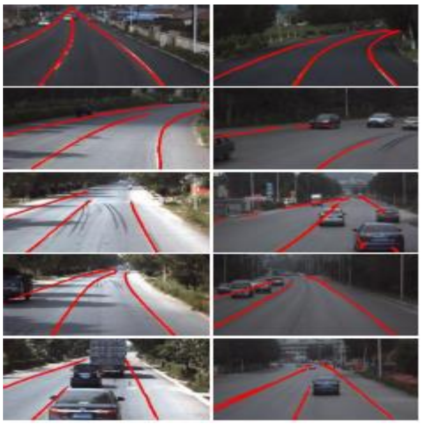

Fig -2: Lane detection using LSTM-CNN network[12]

Zou, Qin et al. proposed in [12] network by fusing DCNN and DRNN together to accomplish the lane detection task. CNN processes each of input image and generate time series of feature map that act as input to LSTM network of lane prediction. The output of LSTM is them fed into the decoder CNN to produce a probability map for lane prediction. The lane probability map has the same size of the input image. ConvLSTM block is embed between SegNet and UNet encoder-decoder network. Feature extracted from multiple frames give more precise and reliable lane contour compared to single frame lane prediction.

2.3 Pedestrian Detection

In Urban environment roads are regularly shared with pedestrian. While zebra crossing and traffic signal can be utilised to regulate pedestrian crossing in-evidently there can be fatal accident involving pedestrian. Complexity and diversity of pedestrian posture and weather condition further complicates the task.

Li, Guofa et al. proposed in [13] CNN model with MobileNetV2 as backbone network using Depthwise seperable convolution instead of standard convolution that reduces computational cost by factor of eight. Priori boxes were utilized to improve precision. The model was specifically trained and tested considering hazy weather condition.

(a) Image (b) ERFNet Segmentation

Fig -3: Pedestrian detection using segmentation[20]

Brehar, R. et al. proposed in [14] method for real time infrared pedestrian segmentation using ERFNet. Use of infrared images allowed model to detect pedestrian in low illumination condition.

2.3 Traffic Sign Detection

Traffic signs aid in visually communicating actions that are permissible and forbidden on driving routes.

Fig -4: Traffic sign detection using YOLOv5[23]

Qin, Zhongbing and Wei Qi Yan proposed in [15] two phase approach for detecting traffic sign. In first phase traffic sign is located from natural background .In second phase traffic sign is categorized based on subclass. A comparative study was performed between Faster-RCNN[16] with VGG16 [17]as basic convolution layers for feature extraction against YOLOv5[18].Faster R-CNN had achieved a higher accuracy rate than YOLOv5.YOLOv5 achieved superior processing time per frame result.

2.3 Animal detection

Vehicle interact with the animal in surrounding environment. Presence of road animals in surrounding environment do not impede traffic movement .Driver only needs to be alerted when they obstruct trajectory of car path on road.

Fig -5:Animal detection in low light condition

Gupta, Savyasachi et al. proposed in [19] Mask R-CNN[20] model with ResNet-101[21] backbone to detect and identify animal such as cow and dog. Centroid based tracking algorithm is used to track movement of animal and is compared to midpoint of lane to determine whether animal obstructs car path.

3. Applications in Vehicle Surveillance

Vehicle surveillance is used by government agency in order to monitor and enforce traffic laws. Continuous monitoring of road traffic has significantly reduced traffic accident. They provide authorities real time situational awareness of vehicle state such as speed, identity and location to aid efficient decision making[22].

3.1 Traffic Surveillance

Traffic monitoring centers are dependent on human operators to track the nature of traffic flows and oversee incident happening on the roads. It can help detect and reduce traffic violation such as over speeding and lane violation. Monitoring multiple CCTV cameras to analyze traffic solution becomes extremely difficult. Integrating automation can reduce workload on human operator and reduce error that are caused by fatigue. Camera based traffic monitoring have become widespread due to its cost-effectiveness and ease of rapid scale deployment[22].

Fig -6: Trafic queue detection using YOLOv4(left) and Mask RCNN(right)[15]

Mandal Vishal et al. in [22] used Mask RCNN[20] and YOLOv4[18] model to detect traffic congestion queue . Mask RCNN provided better precision due to its ability to obtain pixel wise segmentation against bounding rectangular boxes of YOLOv4 model that covers area that are both congested and non congested .

Detecting vehicle on road can help us to monitor their speed and count number of vehicle. Wang, Hai et al.[23] compared two staged detector such as faster R-CNN[16], R-FCN[24], against single stage detector such as SSD[25], RetinaNet[26], and YOLOv3[27] for vehicle detection. The two staged detector are accurate in detecting vehicle at distance .R-FCN had excellent generalization capability to detect vehicle in night and rainy weather condition.YOLOv3 and SSD have fast detection speed that allows them to be utilized in real time image processing. Table 1 compares object detection model summarizes result obtained on on the KITTI data and analyze the obtained results.

Method	Accuracy	Sensitivity	Specificity	Complexity
FasterR-CNN	Medium	Medium	Low	High
R-FCN	High	Low	High	High
SSD	Low	High	High	Low
YOLOv3	Low	High	Medium	Low
RetinaNet	High	Medium	Low	Medium

Fig -7: Result of comparative study of detection model on KITTI dataset [17]

Data generated from continues monitoring can help us determine traffic density which can aid in traffic management. It can give insight of future traffic growth and necessary infrastructure required to reduce traffic congestion[15].

3.2 Licence Plate Detection and Recognition

A licence plate of attached to vehicle that is used by government agency for identification purpose around the world. It plays crucial role in in criminal investigation helping authorities pinpoint the suspect from CCTV surveillance footage.

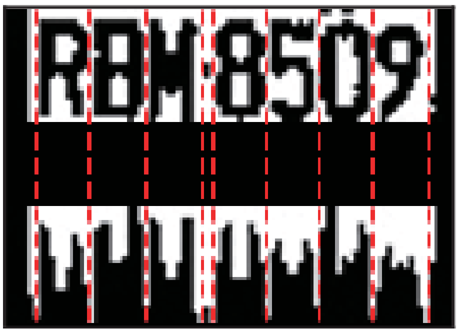

Fig -8: Licence plate g character detection[17]

Lin C. et al. [28] proposed hierarchical process to recognize Licence plate. YOLOv2[18] is used to detect vehicle. Vehicle detection is performed to avoid misidentifying traffic signs or advertisements as license plates.It eliminates many false positive result. After Capturing vehicles SVM is used to detect vehicle's license plates.After capturing license plates, the image is binarized to filter out noise. Horizontal projection is performed to remove upper and lower border of licence plate. a vertical projection on the license plate image is performed to locate the position of each character and then divide it into single characters.LPRCNN model is used to identify blurred and skewed character

3.3 Vehicle Detection from UAV Imagery

UAVs have higher mobility, wider field of view .They can devployed for suvellence without need to set up survellence infrastucture. They can even be used for military survellence behind enemy lines. The solution proposed to should be invariant to size as size of vehicle directly corresponds to altitude of UAV .The solution also should exhibit rotation invariance due to as vehicle may be parked in different orientation.

Ammour N. et al. proposed in [29] four phased approach. The authors used Mean-shift algorithm to segment location where car are likely present. This approach significantly reduce computation due to reduced search space. The proposed region is fed pre-trained VGG16 CNN for feature extraction. Using extracted feature binary SVM classifier is trained to detect presence of car. Morphological dilation is utilised to fine tune detection result.

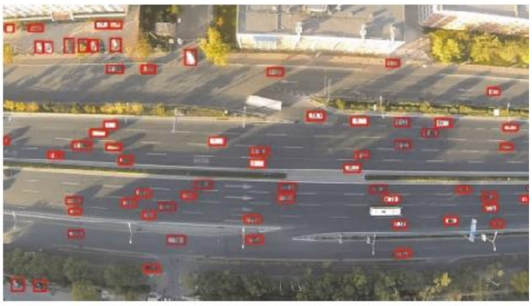

Fig -9: Vehicle localization using UAV images[30]

Yongzheng, Xu et al. in [30] used Faster-RCNN [16]to detect vehicle from aerial surveillance. Faster-RCNN is two staged object detection network and has higher accuracy than single staged object detection model like SSD [25]and YOLO[28]. It was found robust to cars in-plane rotation and illumination changes .This can be be useful for detecting car in shadowed area .

3.4 Vehicle Damage Detection

Car insurance companies around the world have to deal with insurance claim. The manual process on damage validation is time consuming and error prone. In rental car industry inability to detect damage may result in financial loss as company might fail to recover repair cost from customer. Human eye may miss minor damage that may be detected by machine learning model. The machine learning model trained should handle different illumination condition and camera orientation.

Fig -10: Detected damage on car body using Mask-RCNN[31]

Dhieb Najmeddine et al. proposed in [31] Mask-RCNN [20] algorithm with Resnet-101[21] network models a backbone, to detect and segment damaged areas of automobiles. Segmentation at pixel-level gives better localization of damage compared to bounding box due to better precision. The model also predicted severity of damage for better claim assessment.

4. **AUTONOMOUS VEHICLE**

Autonomous car have ability of sensing environment and moving safely without human intervention.Self-driving cars will greatly improve road safety and reduce traffic congestion. This car have ability to communicate with other cars and surrounding infrastructure.

Autonomous car uses LiDAR ,RADAR and Camera in order to capture visual input. LiDAR are costly but they provide accurate 3-D depth information. RADAR are cheap and detect objects in adverse weather condition. Camera can capture input in RGB and infrared channel but are reliable in extreme weather. They also have multiple mechanical and electronic sensor to perceive surrounding environment..

The Society of Automotive Engineers (SAE) defines various automation level based on functionality and amount of human intervention needed. Level 0 vehicle requires driver to take complete control of vehicle. Level 1 provides driver minimum assistance such as Adaptive cruise control and anti-lock braking system (ABS).Level 2 provides driver assistance when vehicle is driven on predominately straight path such as from steering assistance using lane detection .Level 3 vehicle take over driving functionality completely under constant driver supervision. Autonomous system can sense surrounding factors like pedestrian and adjacent cars. Driver must be alert in case of system failure to override it. level 4 has similar capability as level 3 however they do not require active driver attention as autonomous system is designed to handle failure scenario. level 5 cars can be considered truly autonomous system. They will not be equipped with steering wheels and braking pads giving driver no control over vehicle[32].

Cars having level 2 automation feature such advanced driver assistance systems (ADAS) are already available for market sale. Auto manufacturer such as Honda have launched car with level 3 automation. Cars with Level 4 automation are in prototype phase and are expected to be ready for public use within next decade.

Currently no country has permitted license to self driving car. However country like Germany and USA have started to adapt legislation slowly allowing autonomous driving vehicle under limited condition. There are still legal and ethical question raised against autonomous car that needs to be addressed before complete adaption .Definition of responsibility in case of accident is one of the major hurdle that needs to be handled. Complete reliance on capabilities of vehicle may bring negative consequence on automation failure. Drivers' attitudes towards the vehicle manufacture public opinion and social influence will play crucial role building trust in technology[33].

5. CHALLENGES

While intelligent computer vision solution help in reducing human induced error and automate task .The proposed solution should be trained to handle different weather condition and illumination level .Accurate licence plate detector along with smart traffic monitoring system may allow authorities to track every movement of citizen raising privacy concern. Data generated by these system can be used by vehicle manufacture without user consent for commercial gains. Application like driver drowsiness detector and autonomous car should be highly tested in real life scenario before deploying for public use. Proprietary nature of technology may hamper widespread adaption. Trust in technology can play major hurdle in technology adaption of AI driven solutions[33].Legal issue related to autonomous car should also be addressed before public adaption. Machine learning model trained to solve must generalize to real life environment. Continuous research in computer vision field will slowly address reliability concern.

6. CONCLUSIONS

The adaption of compute vision driven solution in mobility domain will greatly improve user experience of driver. It provides high scalability with low equipment cost .Application like autonomous car will revolutionize mobility industry making road transport more safe and pleasurable. Challenges arise with integration of machine driven solution in human life that needs to be addressed before widespread adaption of technology. Greater transparency regarding machine learning driven solution will enhance user trust and will result in faster adaption of technology. Continuous investment in technological research will slowly address reliability issue and will ultimately benefit business and people in long run.

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