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Advanced Driver Assistance System

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Abstract

In order to improve vehicle driving safety in a low-cost manner, we used a monocular camera to study a lane-changing warning algorithm for highway vehicles based on deep learning image processing technology. We improved the mask region-based convolutional neural network for vehicle target detection. Suitable anchor frame ratios were obtained by means of K-means++ method clustering for 66,389 vehicle targets with the width/height ratio, which is one more set of anchor frames than the original setting, so as to ensure that the generation accuracy of candidate frames can be improved without sacrificing more network performance. Using the vehicle target annotation set, we trained the vehicle targets. Through the analysis of indicators for mean average precision, a new set of anchor frames was added to improve the accuracy of vehicle target detection. Based on the improved vehicle detection network and an end-to-end lane detection network in series, we proposed an algorithm for the detection of highway vehicle lane-changing behavior with the first-person perspective by summing the inter-frame change rates in the vehicle lane-changing data pool..

Introduction

In recent years, the technology of advanced driver assistance systems has been rapidly developed and applied. However, the current functions of advanced driver assistance systems configured by vehicles on the road are uneven, and some lack basic driving assistance functions, such as collision avoidance warning and lane-changing warning functions. In addition, 18% of road traffic accidents and 10% of delays are caused by unsafe lane-changing behavior in China [**1**]. A large proportion of straight driving sections under highway conditions and long-term driving under good road conditions will make the driver fatigued and more likely to cause an accident. Therefore, it is beneficial to improve vehicle safety by the early warning of lane-changing behavior of the preceding vehicles. How to improve the driving safety of these vehicles in a low-cost manner and realize the development of the corresponding functions of the driving warning system have important research value. Due to the low-cost and easy deployment of the monocular camera, it can complete the detection and positioning tasks of all targets in the detection module of the warning system. Therefore, based on a monocular camera, we used deep learning image processing technology to research and develop the vehicle lane-changing warning system. The warning system realized perception of the surrounding environment by a low-cost monocular camera. The basic environmental information of the road should include vehicle information and lane information. Through the deep learning pre-processing module, the information of preceding vehicles and the lane information of the ego-vehicle were obtained and combined with the analysis of a lane-changing warning post-processing module to obtain warning information of dangerous road conditions, which improve the driving safety of the ego-vehicle.

Due to the parallel computing wave triggered by deep learning in recent years, a large number of algorithms based on deep learning methods have emerged in the field of target detection. Region-based Convolutional Neural Networks (R-CNNs) were proposed by Girshick et al., in 2014, which combines the region proposal with the image feature convolutional neural network to improve the detection accuracy [**2**]. The proposed region size was re-adjusted and used as the input of the standard CNN architecture [**3**], such as Alexnet [**4**], Visual Geometry Group Network (VGG), Inception, and Deep Residual Network (ResNet). Among them, the last layer of the CNN network architecture was trained using the Support Vector Machine (SVM) algorithm to detect whether there is a target of one of the target classes in the region. According to a linear regression model, the bounding box obtained by the region proposal could further converge to the real bounding box. However, the R-CNN method did not achieve the end-to-end learning.

Literature Survey

In 2015, Girshick et al. proposed an improved algorithm for R-CNN—Fast R-CNN [**5**], which only performs CNN inference once, greatly reducing the amount of calculation. A new pooling technology, Region of Interest (RoI) pooling, was introduced. According to the regional suggestions, CNN features were pooled together. In this way, after the reasoning of the CNN network, the features obtained in the pooling step would form a set. The advantage of this approach was that the end-to-end learning can be achieved, thus avoiding the use of multiple classifiers. The previous SVM classifier was replaced by a Softmax layer, but still required a lot of computing power because it still proposes a selective search area.

In 2016, Ren et al. proposed Faster R-CNN [**6**], which replaces selective search with a CNN framework such as VGG and Inception. A Region Proposal Network (RPN) was proposed. RPN is a fully convolutional network that can achieve the end-to-end learning. The most important breakthrough was to make the RPN network and the object detection network share the convolutional features, which realizes the area proposal with almost no computational cost and reduces the computational time.

Mask R-CNN was proposed by He et al., in 2017 [**7**], and made two improvements on the basis of Faster R-CNN. The RoI pooling layer was replaced with anRoI align layer, and a mask branch was added to predict the segmentation mask of each region of interest. Because the RoI align layer used bilinear interpolation, the output of RoI was aligned with the source image, resulting in more accurate instance segmentation. Because the mask branch was operated in parallel with the original classification branch and the border regression branch, time loss was reduced and the segmentation accuracy was improved.

In terms of research on algorithms for detecting lane-changing behavior, there is a method based on a third-person fixed perspective. By detecting the angle between the trajectory of the target vehicle and the fixed lane line, when the angle is greater than a certain threshold, it is determined that the target vehicle has changed lane. Shi et al. [**8**] calculated the variance of the lateral distance between the target vehicle's trajectory line and the corresponding points of the ego-vehicle's lane line based on the third-person fixed perspective, and determined the lane-changing behavior based on this. Although it is possible to send lane-changing warning information to the driver of the ego-vehicle through third-party observation and through the internet of vehicles, it requires a large number of cameras beside the road, and the threshold for drivers to use is relatively high. Hu [**9**] proposed an algorithm for extracting the edge feature of the lane line with a direction-tunable filter, using a Kalman filter to track and correct the parameters of the lane line, and proposed a vehicle lane-changing detection method based on the lane. Wei et al. [**10**] proposed a lane-changing detection method for vehicle violation based on the actual behavior of the vehicle crossing the solid line. Zhao et al. [**11**] proposed a vehicle merging warning system with a preset safety zone. When the midpoint of the vehicles on both sides of the ego-vehicle lane crossed the trapezoidal safety zone of the ego-vehicle, the warning message was prompted. The above methods all determined the result of the lane-changing, failed to meet the requirement of real-time warning to a large extent, and could not feedback in a timely manner the lane-changing information of the preceding vehicles.

A good prediction for the lane-changing actions of surrounding vehicles will significantly improve the safety and passenger comfort of driver-assisted and automated vehicles [**12**]. Woo et al. [**13**] installed a position sensor and six lidars on the ego-vehicle to obtain the positions and speeds of four adjacent target vehicles, used SVM to estimate the driver's intention, and predicted the target vehicle's trajectory to detect lane-changing behavior. Zhang et al. [**14**] used the relative speeds and distance data of the target vehicle and four adjacent vehicles to simulate the lane-changing behavior of the target vehicle with a continuous hidden Markov model, calculated the lane-changing probability, and predicted the lane-changing behavior of the target vehicle, which reached 85% of the true positive rate. Zhang et al. [**15**] used a passive-aggressive algorithm to design a lane-changing source classifier with a large number of lane-changing operations as training samples according to the motion state of the target vehicle before the lane change and the parameters of the relative motion with the surrounding vehicles, and proposed an online transfer learning strategy to predict the lane-changing intention of the target vehicle. This method requires an ego-vehicle equipped with a GPS and millimeter-wave radar. Based on the data provided by radars and cameras, Lee et al. [**16**] input a simplified bird's-eye view into a convolutional neural network to predict the lane-changing intention of the target vehicle. Wei et al. [**17**] proposed a deep residual learning neural network to identify the lane-changing behavior of the vehicle on a highway based on images captured by a forward-facing vehicle camera and measured ego-vehicle braking and accelerator pedal forces, speed, steering angle, and longitudinal and lateral acceleration information, achieving an accuracy of 87%.

In summary, the research on the vehicle lane-changing warning algorithm is partly based on the determination of the lane-changing result, which leads to the inability to feedback in a timely manner the lane-changing information of the preceding vehicles, or is based on the lidar or the radar and camera to obtain the relative motion parameters between the ego-vehicle and the target vehicles, which leads to high hardware cost, and the recognition accuracy needs to be further improved. In order to realize the lane-changing warning of the ego-vehicle in a low-cost way to improve the safety of the driver assistance system, we studied the lane-changing warning algorithm based on a monocular camera. The current mainstream target detection frameworks such as Mask R-CNN are multi-target detection networks, which are not optimized for single target detection tasks such as vehicle detection. We improved the generation process of the candidate frame of Mask R-CNN by counting the relevant size parameters of the vehicles, so as to obtain a better candidate frame and improve the detection accuracy of the target vehicles. We proposed to calculate the sum of the inter-frame change rate when the target vehicle changes lane based on the first-person perspective. We could remind the driver in a timely manner to pay attention to dangerous lane-changing behavior by determining the target vehicle's lane-changing behaviors instead of the lane-changing results, and we achieved a high lane-changing detection accuracy.

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Existing System

It utilizes sensors to detect and warn motorists about approaching cars in adjacent lanes. Lane Change Assist can help warn of vehicles approaching your blind spots, which can prevent lane change accidents on the road. When LCA senses that you are going to change lanes in a way that might be dangerous, it will provide an audible and/or visual warning to help you make a safe lane change.

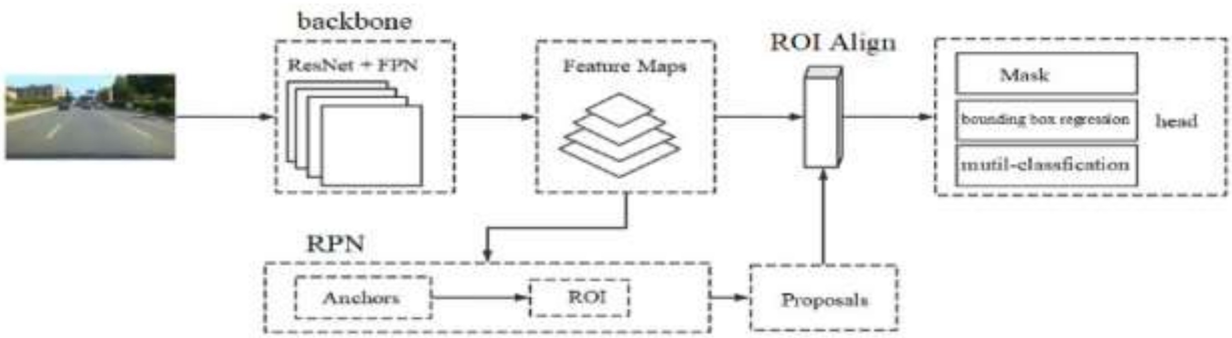
In the existing system, When drivers signal for a lane change on multi lane highways and roads, it checks blind spots on the corresponding side and to vehicle's rear to look for existing or approaching risks. If its unsafe to change into the lane, the LCA system will provide an audible or visual warning to the driver.

Proposed System

Video files of cars on a road are used as a dataset in this project. Also, detecting cars in an image when the distance between two vehicles are less then it alerts to the driver that change lane in voice as well message.

In this, we use an HSV frame obtained from the frame captured by cv2.VideoCapture() to highlight only the points at which cars are making a turn and blackout the remaining road & cars moving straight on the road. Upper and Lower Thresholds are set to define the range of color in HSV to see the points at which the car is changing lanes and to be used as a mask for the frame. The canny edge detector is used with Hough Line Transform for the detection of lanes.

System Architecture



Methodology

The K-means algorithm is a distance-based clustering algorithm that uses the distances between points as an indicator of similarity. If the distance between two pixels is closer, the similarity is higher. This algorithm gathers points that are close to each other into a cluster, and finally obtains compact, bounded, and independent cluster objects. The inherent defect of the K-means algorithm is that it needs to manually specify the number of cluster points. The K-means algorithm is more sensitive to the location of the starting point. The K-means++ algorithm compensates for these defects to a certain extent. It can speed up the convergence of the model and improve the positioning accuracy of the target by using K-means++ clustering to obtain more suitable anchor frame ratios of vehicle targets. A higher positioning accuracy is used to meet the need of accurate vehicle lane-changing detection.

Vehicle Lane-Changing Detecting Algorithm

Combining the improved vehicle detection network and the end-to-end lane detection network in series , the integrated outputs were obtained. We proposed a lane-changing detection method based on the first-person perspective, which can discriminate the target vehicle's lane-changing behavior and obtain a higher detection accuracy.

The proportion of straight driving sections in the highway driving conditions is very large, and driving under good road conditions for a long time will make the driver tired and easily cause accidents. Therefore, it is necessary to inform the driver of the lane-changing behavior of the preceding vehicles under highway conditions to reduce the accident rate. The lane-changing detection algorithm made the following assumptions: (1) the driver's ego-vehicle was stable without obvious lateral displacement; (2) the driving section was a straight section.

According to the perspective principle, two parallel lane lines will intersect at a point in the distance. If two other parallel lines are added between the two parallel lines, because the fan-shaped area in the two lane lines eventually converge to a point, the other two parallel lines eventually converge to the same intersection. Thus, the four parallel lanes will eventually converge to a point P_0 (P_1) in the distance.

Conclusions

In this project, a small demonstration of smart car navigation is explored using the lane change detection method.

Computer Vision is rapidly growing and its applications are advancing in local navigation of automobiles

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