International Journal of Scientific Research & Engineering Trends
Volume 5, Issue 6, Nov-Dec-2019, ISSN (Online): 2395-566X

Traffic Sign Recognition and Boundary Estimation Using Convolutional Neural Network

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Abstract **- Nowadays, a large number of vehicles is quickly increasing. In parallel, the number of routes and traffic signs has developed. As an outcome of developed traffic signs, the drivers are required to learn all the traffic signs and to pay attention to them while driving. A method that can automatically identify the traffic signs has been required to decrease traffic accidents and to drive more easily. Recognition and Detection of texts in traffic signs have been extensively studied and with the advance in image capture technology has accommodated to develop or to produce new methods to resolve this issue. In this work, we introduced a method for detection, segmentation and recognition of text-based traffic signs from images analyzing and processing techniques. We introduce a unique traffic sign detection system that concurrently estimates the location and precise boundary of traffic signs using convolution neural network (CNN). Estimating the precise boundary of traffic signs is very important in navigation systems for smart vehicles where traffic signs can be used as 3-D landmarks for the road environment. In this paper, the boundary view of a traffic sign is formulated as 2- D pose and shape class prediction problem, and this is completely solved by a single CNN. With the predicted 2-D pose and the shape class of a targeted traffic sign in the input, we determine the actual boundary of the destination sign by projecting the boundary of a corresponding template sign image into the input image plane.**

Keywords- **Traffic sign detection, traffic sign boundary estimation, convolution neural network..**

I. INTRODUCTION

In all countries of the world, the relevant information about the road limitation and condition is shown to drivers as visual signals, such as traffic signs and traffic paths. Traffic signs are an essential part of road infrastructure to give information about the current status of the road, limitations, prohibitions, warnings, and other helpful information for navigation.

Traffic sign detection has been a fabulous problem for intelligent vehicles, particularly as a leading step for traffic sign recognition which contributes useful information such as directions and alerts for self-governing driving or driver assistance operations.

Newly, traffic sign detection has received another attention from navigation systems for smart vehicles, where traffic signs can be used as separate landmarks for mapping and localization. Separate from natural landmarks such as corner edges which have arbitrary representation, traffic signs have conventional appearances such as shapes, colors, and models defined by strict directions. The standard representations of traffic signs make it effective and strong to identify and match traffic signs under different situations, and this forms the main reason that traffic signs are an excellent choice as milestones for road map reconstruction. Early traffic sign detection systems do not satisfy this requirement as they only estimate bounding boxes of traffic signs. Pixel wise forecast methods such as semantic image segmentation, which have been implemented successfully for road views, can be an option for boundary estimation. However, it needs time-consuming algorithms that can seriously harm the appearance of real-time systems for smart vehicles.

To overcome this incompetence, we suggest a traffic sign detection system where the state and precise boundary of traffic signs are predicted simultaneously using a single convolution neural network (CNN). Our novel object detection network is based on the recent advances in CNN based object detection for object bounding box prediction.

Using the predicted 2D poses and shape labels, the boundary edges of a traffic sign are computed by proposing the boundary edges of a corresponding template image of the sign into the image coordinate using the predicted pose, as illustrated in Fig 1. By utilizing the templates of traffic signs, the proposed system efficiently employs strong prior information of

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destination shapes. This allows robust boundary estimation for traffic signs that are occluded or blurry, which is regularly challenging in pixel-wise prediction such as contour estimation and segmentation. As a result, our method obtains detection rates higher than 0.88 mean average precision (mAP), and boundary estimation error less than 3 pixels with respect to the input resolution of 1280 × 720 pixels.

Fig.1. Boundary estimation using a predicted 2D pose and a shape label: 2D poses and shape labels are predicted from CNN.

II. EXISTING SYSTEM

Generally, traffic sign identification contains two parts: detection and classification. The goal of detection is to identify the locations and sizes of the current traffic signs in an image, and the task of classification is to indicate a class label to each detected traffic sign.

1. Traffic Sign Detection

Most of the earlier works on traffic sign detection rely on handcrafted image features to recognize destination signs. Different combinations of features and classifiers are intended to track a robust and fast traffic sign detector, and near 100% accuracy is obtained on short benchmark dataset such as German Traffic Sign Detection Benchmark (GTSDB) dataset. Since running a difficult feature extractor and a classifier is time-consuming, multi-stage cascade architectures composed of active candidate exploration and perfect candidate classification have been a typical pipeline of traffic sign detection. For the initial stage of detection pipeline, simple but powerful features such as color and edge are used to extract a number of applicant regions. Color is one of the most distinctive characteristics of traffic signs, thus multiple works have utilized color features for fast candidate region search in different forms, such as color probability maps.

2. Traffic Sign Classification

Traffic sign classification is a method of automatically identifying traffic signs along the road, such as speed limit signs, yield signs, merges signs, etc. Signifying capable to automatically identify traffic signs allows us to establish "smarter vehicles". Self-driving vehicles need traffic sign identification in order to accurately parse and follow the roadway. Furthermore, "driver alert" operations inside vehicles need to know the roadway around them to help support and protect drivers. Traffic sign identification is just one of the difficulties that computer vision and deep learning can answer.

III. PROPOSED SYSTEM

The overall scheme of the proposed approach is demonstrated in Fig 2. For the CNN section, any object detection interface structure, which backslides the status of the target object, can be used. In our work, we develop the CNN section based on the SSD structure where forecasts are immediately performed across many feature levels. The main difference of our system with the early detection systems is what it predicts as output: instead of predicting bounding box coordinates, our system performs model estimation, which can be turned into the boundary estimation of corresponding traffic signs.

III. PROBLEM FORMULATION

This study presented an inclusive application of nano fluids for automotive cooling engine vehicles. A vast number of available references showed that nano fluids have a great application prospect in the development of modern engines. For cooling system of radiators, nano particles can be dispersed in the fluid to enhance the thermal conductivity of the liquid. In addition, the presence of nano particles in radiator will also improve the thermal performance and reduce friction.

However, the optimum amount of nano particles still remains unknown. Another method for cooling the automotive engine system is by dispersing nano particles in a conventional coolant radiator. Heat transfer coefficient can be improved up to 50% compared to the original coolant; however, the problem of pressure drop limits the efficiency factor of the cooling system. For this case, most researchers agree that the optimum performance of cooling system can be achieved at low volume fraction of nano particles (b1%). At the same

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time, there are still some problems and challenges regarding the mechanisms of heat transfer enhancement and the actual applications on engine vehicle. Current research on nano fluids for engine cooling system is still at its initial stage and needs further development. Therefore in this study the friction factor and forced convection heat transfer of TiO2 nano particles dispersed in water in a car radiator was numerically determined. Four different nano fluid with different volume concentrations (1%, 2%, 3% and 4%) were used, and the resulting thermal properties were evaluated.

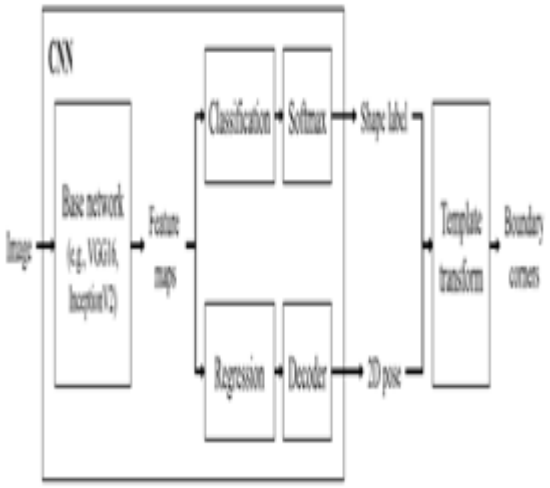

Fig.2. The overall procedure of the proposed method.

In the CNN block, an input image is given to a base system which extracts feature maps using a series of convolution, non-linear activation, and pooling operations. Then from the feature maps, 2D poses and shape selection probabilities are estimated by two distributed convolution layers, specifically, pose regression layer and shape classification layer, joined with progressive operations that transform the convolution outputs to the 2D pose values and class probabilities.

1. Convolution Feature Extraction

As pre-trained CNNs on Image Net categorization task has become dominant as an origin point for fine-tuning CNNs for other vision tasks, most of the freshly proposed object detection methods also hire one of these systems for feature extraction upon which detection layers display bounding box estimation and object category group.

2. 2d Pose Prediction

The initial review of the bounding box regression is done in recent CNN based object detectors. The regression layers, which can be both convolution layers and fully-connected layers, take feature maps from the base interface and predict pose offsets relevant to the default box coordinates.

3. Boundary Corner Estimation

Given the 2D pose of an objective sign, it is straightforward to define the boundary of the sign given its template image. First, from the shape classification layer, we prognosticate the state label of the target to define which template image to utilise. The output of the shape classification layer, indicated by s, is N-way softmax values where N is the number of shape classes like rectangle, diamond, octagon and background in our experiments.

4. Training

All our proposed models are based on base systems that are trained on Image Net dataset. The system parameters are fine-tuned during the training of the complete model. The pose regression and shape classification layers are trained from the mark with 'Xavier' initialization. To prepare the pose regression and shape classification layers, we define positive and negative samples and use them to calculate a loss function.

IV. EXPERIMENTAL RESULTS

1. Implementation

The proposed pose regression layer can be linked with various modern object detection systems such as Faster RCNN and SSD. We especially chose to implement our models on top of the SSD framework since it is significantly superior to Faster R-CNN in terms of computational efficiency while being competitive inaccuracy.

2. Experimental Setup

All the training process was directed using Caffe framework. For the experiment, we performed the system using Snapdragon Neural Processing Engine (SNPE) SDK which presents an optimized implementation of CNN forward propagation on the Qualcomm Snapdragon TM 820A processor2 with GPU utilization. For both training and testing, we used RGB channel color images, and various image resolutions for the base network are tested to estimate the trade-off between accuracy and speed.

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Fig. 3. Input Image.

Fig .4. Traffic image and its corresponding grayscale image.

Fig .5. Edge detection.

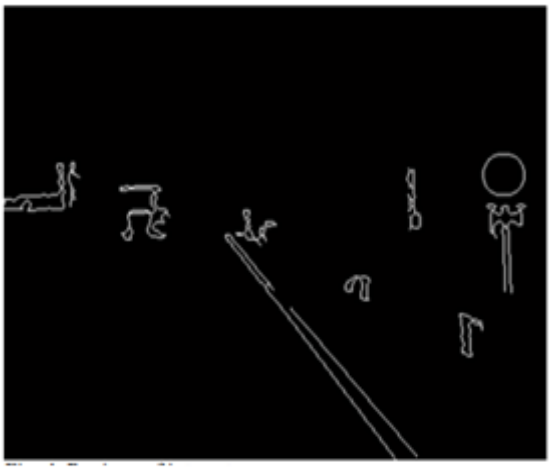

Fig .6. Regions of interest.

3. Comparison with Segmentation Based Methods

Examine the boundary estimation accuracy of our system with a segmentation-based method connected with bounding box detection. For the segmentation-based method, the corresponding detection results are accepted with our method except for the results for the segmentation-based method are represented by bounding boxes like circumscribed rectangles of template vertices.

4. Sign Boundary Refinement

Though our designs present robust boundary estimation for traffic signs, we recognized that the efficiency can be increased further with an image-based local culture by using the edge or gradient of sign frames. In the learning process, we estimate the gradient image for the spot of a detected traffic sign, and then decide an optimal 2D transform that decreases the weighted distance between the estimated gradient image and the predicted boundaries from our system.

V. CONCLUSION

In this paper, we introduced the dynamic traffic sign detection system where areas of traffic signs are determined together with their precise boundaries. To this end, we concluded the object bounding box detection difficulty and formulated an object pose evaluation problem, and the problem is effectively modeled using CNN based on the recent advances in object detection systems. The predicted pose of traffic signs is used to modify the boundary of traffic sign templates into the input image plane, presenting precise boundaries with high efficiency. To obtain practical detection speed, we explored the best-performing base systems and clipped unnecessary layers of the network by considering the characteristics of traffic signs. Besides, by optimizing the resolution of network input for the best tradeoff between speed and accuracy, our indicator can run with frame rate of 7 FPS on less-power mobile platforms.

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