

Real Time Indian Traffic Signboard Recognition And Driver Alert System Using CNN

B.Vinoth¹, V.Shenbagapriya²

¹Dept of Computer Applications

²Assistant Professor, Dept of Computer Applications

^{1,2}B.S Abdur Rahman Crescent Institute of Science & Technology, Vandalur, Chennai

Abstract- Traffic signs recognition (TSR) is an important part of some advanced driver-assistance systems (ADASs) and auto driving systems (ADSs). As the first key step of TSR, traffic sign detection (TSD) is a challenging problem because of different types, small sizes, complex driving scenes, and occlusions. In recent years, there have been a large number of TSD algorithms based on machine vision and pattern recognition. In this paper, a comprehensive review of the literature on TSD is presented. We divide the reviewed detection methods into two main categories: sign based methods, shape-based methods. The proposed method is broadly divided into, data processing, data classification, and training and testing. System uses variety of image processing techniques to enhance the image quality and to remove non-informational pixel, and detecting edges. Feature extractors are used to find the features of image. Advanced machine learning algorithm Convolutional Neural Networks (CNN) is used to classify the different traffic sign images based on their features by using the real time camera.

Keywords- Deep Learning, CNN, Traffic Sign, Detection, Auto Pilot Vehicles.

I. INTRODUCTION

Currently, more and more intelligent transportation systems are developed for assisting drivers. Traffic sign recognition (TSR) is extremely important for safe and careful driving, as not only can this system inform the driver of the conditions of the road, but can also support the driver during the tedious task of remembering each of the many types of traffic signs. Some of the traffic sign information may sometimes be extracted from the GPS navigation data, but it is always neither complete nor up-to-date. Moreover, temporary speed limits for road works, as well as variable speed limits, are by registration not included in predefined digital cartographic data. Therefore, a visual real-time TSR system is a mandatory complement to GPS systems for designing advanced driving assistance systems. Traffic signs are designed using specific shapes and colors, which are highly salient and visible from the background against which they are set, enhancing their visibility to drivers. In-depth study of

traffic sign datasets allows us to observe some common characteristics of traffic signs. In this paper, we propose a novel graph-based ranking and segmentation approach to detect salient regions, with specified colors, as traffic sign candidate regions. The proposed approach combines information pertaining to the colour, saliency, spatial, and contextual relationship of nodes for traffic sign detection, making it more discriminative and robust than other methods in addressing various illumination conditions, shape rotations, and scale changes of traffic sign images.

II. LITERATURE REVIEW

1. Fixation distance and fixation duration to vertical road signs Marco Costaa,*, Andrea Simoneb, Valeria Vignalib, Claudio Lantierib, Nicola Palenac-2018.

This paper proposes a threshold based method use First-fixation distance was linearly related to speed and fixation duration. Road signs were gazed at a much closer distance than their visibility distance. In a second study a staircase procedure was used to test the presentation-time threshold that lead to a 75% accuracy in road sign identification. The threshold was 35 ms, showing that short fixations to a road signs could lead to a correct identification.

2. An overview of traffic sign detection and classification methods-Yassmina Saadna1 · Ali Behloul1-2017.

The present paper introduces an overview of some recent and efficient methods in the traffic sign detection and classification. Indeed, the main goal of detection methods is localizing regions of interest containing traffic sign, and we divide detection methods into three main categories: color-based (classified according to the color space), shape-based, and learning-based methods (including deep learning). In addition, we also divide classification methods into two categories: learning methods based on hand-crafted features (HOG, LBP, SIFT, SURF, BRISK) and deep learning methods. For easy reference, the different detection and classification methods are summarized in tables along with the different datasets. Furthermore, future research directions and

recommendations are given in order to boost TSR's performance.

3. Traffic Sign Detection Using a Cascade Method With Fast Feature Extraction and Saliency Test Dongdong Wang, Xinwen Hou, Jiawei Xu, Shigang Yue, Member, IEEE, and Cheng-Lin Liu, Fellow, IEEE-2017.

In this paper, they propose a fast traffic sign detection method based on a cascade method with saliency test and neighboring scale awareness. In the cascade method, feature maps of several channels are extracted efficiently using approximation techniques. Sliding windows are pruned hierarchically using coarse-to-fine classifiers and the correlation between neighboring scales. The cascade system has only one free parameter, while the multiple thresholds are selected by a data-driven approach. To further increase speed, we also use a novel saliency test based on mid-level features to pre-prune background windows. Experiments on two public traffic sign data sets show that the proposed method achieves competing performance and runs 2~7 times as fast as most of the state-of-the-art methods.

4. Fast Detection of Multiple Objects in Traffic Scenes With a Common Detection Framework Qichang Hu, Sakrapee Paisitkriangkrai, Chunhua Shen, Anton van den Hengel, and Fatih Porikli-2017.

In this paper, they focus on three important classes of objects: traffic signs, cars, and cyclists. We propose to detect all the three important objects in a single learning-based detection framework. The proposed framework consists of a dense feature extractor and detectors of three important classes. Once the dense features have been extracted, these features are shared with all detectors. The advantage of using one common framework is that the detection speed is much faster, since all dense features need only to be evaluated once in the testing phase. In contrast, most previous works have designed specific detectors using different features for each of these three classes.

5. Traffic Sign Occlusion Detection Using Mobile Laser Scanning Point Clouds Pengdi Huang, Ming Cheng, Member, IEEE, Yiping Chen, Huan Luo, Cheng Wang, Senior Member, IEEE, and Jonathan Li, Senior Member, IEEE-2017.

This paper presents a novel traffic sign occlusion detection method using 3-D point clouds and trajectory data acquired by a mobile laser scanning system. To produce a maintenance guide, our method aims to obtain the degree of occlusion by analyzing the spatial relationship between traffic

signs, surroundings, and drivers on the road. First, a detection method considering both reflectance and geometric features is developed to capture traffic signs. Next, to simulate the driver's view, a trajectory-based method is proposed to determine driver's observation location and the corresponding observed traffic sign. Finally, to determine whether a traffic sign is in occlusion, a hidden point removal algorithm is adopted and carried out.

6. Indian sign board recognition using image processing by G.Revathi, Dr.G.Balakrishnan.-2016

This paper proposes a traffic sign recognition (TSR) systems consist of two phases of detection and classification; for some TSR systems, a tracking phase is designed between detection and classification for dealing with video sequences. This paper mainly focused on hog features based traffic sign detection.

III. EXISTING SYSTEM

In this paper, a coarse-to-ne traffic sign detection algorithm with stepwise learning strategy is proposed to improve the detection speed and accuracy for high-resolution images and small targets. Firstly, the proposed algorithm meshes the input image, then uses the target grid prediction network to detect whether the grid contain a target. According to the grid prediction results, we flexibly extract the potential target regions to completely cover the real targets. Finally, SSD is utilized to detect the traffic signs on the potential target regions. The target grid prediction is based on a concise convolutional neural network, which can quickly and accurately locate the approximate position of the target and remove the background from the searching space.

EXISTING TECHNIQUE :DEEP LEARNING

TECHNIQUE DEFINITION:

DEEP LEARNING:

Deep learning is a subset of machine learning where artificial neural networks, algorithms inspired by the human brain, learn from large amounts of data. Deep learning allows machines to solve complex problems evenwhen using a data set that is very diverse, unstructured and inter-connected.

DRAWBACKS:

- This system is worked based on prototype images.
- Due to prototype the system needs more advancement.

IV. PROPOSED CONCEPT

We proposed the traffic sign detection methods by using deep learning classification based methods. In recent years, with the development of deep learning based detection methods (CNN) have gradually become the mainstream algorithms and achieved the-state-of-the-art results in some aspects. The CNN (CONVOLUTIONAL NEURAL NETWORK based TSD (Traffic Sign Detection) methods are reviewed according to their adopted advanced machine learning classification methods.

PROPOSED ALGORITHM: CNN

ALGORITHM DEFINITION: CNN (CONVOLUTIONAL NEURAL NETWORKS):

The convolutional neural network (CNN, or ConvNet) is a class of deep neural networks, most commonly applied to analyzing visual imagery. They have applications in image and video recognition, recommender systems, image classification, medical image analysis, and natural language processing.

ADVANTAGES:

- This system is worked based on real time.
- When compared to existing system this is advanced technique.

V. MODULE DESCRIPTION

1. INPUT IMAGE:

Read and Display an input Image. Read an image into the workspace, using the imread command or by using CAMERA. In image processing, it is defined as the action of retrieving an image from some source, usually a hardware-based source for processing. It is the first step in the workflow sequence because, without an image, no processing is possible. The image that is acquired is completely unprocessed.

2. PREPROCESSING.

Pre-processing is a common name for operations with images at the lowest level of abstraction both input and output are intensity images. The aim of pre-processing is an improvement of the image data that suppresses unwanted distortions or enhances some image features important for further processing. Image pre-processing methods use the considerable redundancy in images. Neighboring pixels

corresponding to one object in real images have essentially the same or similar brightness value. Thus distorted pixel can often be restored as an average value of neighboring pixels.

1. RESIZING THE INPUT IMAGE:

All the input images are resized into same dimensions. If the specified size does not produce the same aspect ratio as the input image, the output image will be distorted.

2. CONVERTING COLOUR FORMAT:

For many applications of image processing, color information doesn't help us. If you get into the business of attempting to distinguish colors from one another, then one reason for converting RGB image to BLACK AND WHITE or GRAYSCALE formats in image.

3. SEGMENTATION

Image segmentation is a commonly used technique in digital image processing and analysis to partition an image into multiple parts or regions, often based on the characteristics of the pixels in the image. In computer vision, Image Segmentation is the process of subdividing a digital image into multiple segments (sets of pixels, also known as super pixels. Segmentation is a process of grouping together pixels that have similar attributes. Image Segmentation is the process of partitioning an image into non-intersecting regions such that each region is homogeneous and the union of no two adjacent regions is homogeneous Pixels in a region are similar according to some homogeneity criteria such as color, intensity or texture so as to locate and identify objects and boundaries (lines,curves,etc) in an image. Segmentation accuracy determines the eventual success or failure of computerized analysis procedure.

1. COLOUR SPACE CONVERSIONS:

Color space conversion is the translation of the representation of a color from one basis to another. This typically occurs in the context of converting an image that is represented in one color space to another color space, the goal being to make the translated image look as similar as possible to the original.

2. MORPHOLOGICAL OPERATIONS:

Morphological image processing is a collection of non-linear operations related to the shape or morphology of

features in an image. Morphology is a broad set of image processing operations that process images based on shapes. Morphological operations apply a structuring element to an input image, creating an output image of the same size.

- A) COMPLEMENT THE IMAGE
- B) HOLES FILLING
- C) DILATION
- D) BORDER CORRECTING

CNN (CONVOLUTIONAL NEURAL NETWORK):

The **Convolutional Neural Networks (CNN)** is one of the most famous deep learning algorithms and the most commonly used in image classification applications. In general, the CNN architecture contains three types of layers, which are convolutional layers, pooling layers, and fully connected layers. The CNN algorithm receives an input image that passes through the layers to identify features and recognize the image, and then it produces the classification result. The architecture of the CNN contains alternating convolutional layers and pooling layers, followed by a set of fully connected layers. The output of each layer in the CNN is the input of the following layer.

Image Input Layer

An image Input Layer is where you specify the image size, which, in this case, is 28-by-28-by-1. These numbers correspond to the height, width, and the channel size. The digit data consists of grayscale images, so the channel size (color channel) is 1. For a color image, the channel size is 3, corresponding to the RGB values. You do not need to shuffle the data because train Network, by default, shuffles the data at the beginning of training. Train Network can also automatically shuffle the data at the beginning of every epoch during training.

Convolutional Layer

In the convolutional layer, the first argument is filter Size, which is the height and width of the filters the training function uses while scanning along the images. In this example, the number 3 indicates that the filter size is 3-by-3. You can specify different sizes for the height and width of the filter. The second argument is the number of filters, num Filters, which is the number of neurons that connect to the same region of the input. This parameter determines the number of feature maps. Use the 'Padding' name-value pair to add padding to the input feature map. For a convolutional layer with a default stride of 1, 'same' padding ensures that the spatial output size is the same as the input size. You can also

define the stride and learning rates for this layer using name-value pair arguments of convolution2dLayer.

Batch Normalization Layer

Batch normalization layers normalize the activations and gradients propagating through a network, making network training an easier optimization problem. Use batch normalization layers between convolutional layers and nonlinearities, such as ReLU layers, to speed up network training and reduce the sensitivity to network initialization. Use batch Normalization Layer to create a batch normalization layer.

ReLU Layer

The batch normalization layer is followed by a nonlinear activation function. The most common activation function is the rectified linear unit (ReLU). Use reluLayer to create a ReLU layer.

Max Pooling Layer

Convolutional layers (with activation functions) are sometimes followed by a down-sampling operation that reduces the spatial size of the feature map and removes redundant spatial information. Down-sampling makes it possible to increase the number of filters in deeper convolutional layers without increasing the required amount of computation per layer. One way of down-sampling is using a max pooling, which you create using maxPooling2dLayer. The max pooling layer returns the maximum values of rectangular regions of inputs, specified by the first argument, poolSize. In this example, the size of the rectangular region is [2,2]. The 'Stride' name-value pair argument specifies the step size that the training function takes as it scans along the input.

Fully Connected Layer

The convolutional and down-sampling layers are followed by one or more fully connected layers. As its name suggests, a fully connected layer is a layer in which the neurons connect to all the neurons in the preceding layer. This layer combines all the features learned by the previous layers across the image to identify the larger patterns. The last fully connected layer combines the features to classify the images. Therefore, the Output Size parameter in the last fully connected layer is equal to the number of classes in the target data. In this example, the output size is 10, corresponding to the 10 classes. Use fully Connected Layer to create a fully connected layer.

Softmax Layer

The softmax activation function normalizes the output of the fully connected layer. The output of the softmax layer consists of positive numbers that sum to one, which can then be used as classification probabilities by the classification layer. Create a softmax layer using the softmaxLayer function after the last fully connected layer.

Classification Layer

The final layer is the classification layer. This layer uses the probabilities returned by the softmax activation function for each input to assign the input to one of the mutually exclusive classes and compute the loss. To create a classification layer, use classificationLayer.

VI. CONCLUSION

In this paper, a comprehensive review of the literature on TSD is presented. We divide the reviewed detection methods into two main categories: color-based methods, shape-based methods. The proposed method is broadly divided in five part data collection, data processing, data classification, training and testing. System uses variety of image processing techniques to enhance the image quality and to remove non-informational pixel, and detecting edges. Deep learning algorithm Convolutional Neural Network (CNN) is used to classify the images based on their features.

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