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Traffic Sign Detection and Recognition Using Open CV

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Abstract

This paper reviews the method for traffic sign detection and recognition. In the section on learning-based detection, we review the Viola Jones detector and the possibility of applying it to traffic sign detection. The recognition of the detected traffic sign is handled by the Histogram of Gradient based SVM classifier. Together this system is expected to perform much better than the other systems available. The algorithms when trained with proper set of images have been noted to perform accurately. This must hold true for the traffic signs as well under different color, lighting, atmospheric conditions.

Key Words

OpenCV, Haar features, Cascades classification, Machine Learning, Histogram of Gradient, Cascade Training, SVM, KNN, Feature matching.

1. INTRODUCTION

In recent years there is increase in computing power have brought computer vision to consumer-grade applications. As computers offer more and more processing power, the goal of real-time traffic sign detection and recognition is becoming feasible. Some new models of high class vehicles already come equipped with driver assistance systems which offer automated detection and recognition of certain classes of traffic signs. Traffic sign detection and recognition is also becoming interesting in automated road maintenance. Traffic symbols have several distinguishing features that may be used for their detection and identification. They are designed in specific colours and shapes, with the text or symbol in high contrast to the background. Every road has to be periodically checked for any missing or damaged signs; as such signs pose safety threats. The checks are usually done by driving a car down the road of interest and recording any observed problem by hand. The task of manually checking the state of every traffic sign is long, tedious and prone to human error. By using techniques of computer vision, the task could be automated and therefore carried out more frequently, resulting in greater road safety. To a person acquainted with recent advances in computer vision, the problem of traffic sign detection and recognition might seem easy to solve. Traffic signs are fairly simple objects with heavily constrained appearances. Just a glance at the well known PASCAL visual object classes challenge for 2009 indicates that researchers are now solving the problem of detection and classification of complex objects with a lot of intra-class variation, such as bicycles, aero planes, chairs or animals. Contemporary detection and classification algorithms will perform really well in detecting and classifying a traffic sign in an image. However, as research comes closer to commercial applications, the constraints of the problem change. In driver assistance systems or road inventory systems, the problem is no longer how to efficiently detect and recognize a traffic sign in a single image, but how to reliably detect it in hundreds of thousands of video frames without any false alarms, often using lowquality cheap sensors available in mass production. To illustrate the problem of false alarms, consider the following: one hour of video shot at 24 frames per second consists of 86400 frames. If we assume that in the video under consideration traffic signs appear every three minutes and typically span through 40 frames, there are a total of 800 frames which contain traffic signs and 85600 frames which do not contain any signs. These 85600 frames without traffic Fig 1. Some examples of Traffic Signs on road. signs will be presented to our detection system. If our system were to make an error of 1 false positive per 10 images, we would still be left with 8560 false alarms in one hour, or two false alarms every second, rendering the system completely unusable for any serious application! To make the problem even harder, we cannot expect the vehicle on which a commercial traffic sign detection system will be deployed to be equipped with a very high-resolution camera or other helpful sensors, as the addition of such sensors increases production costs.

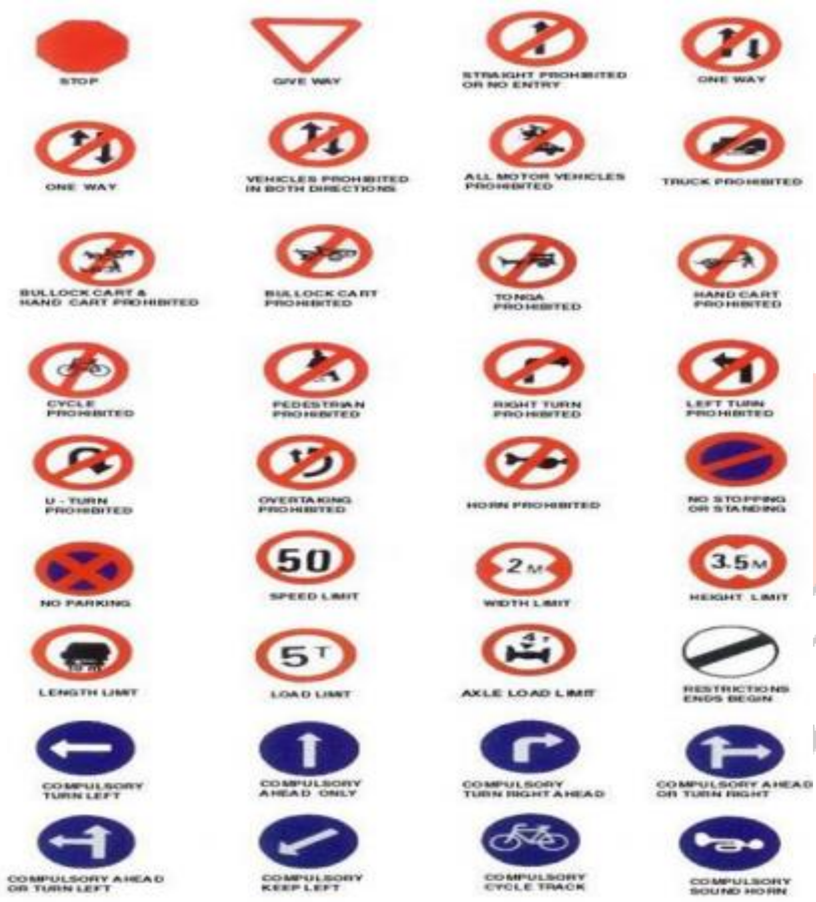

Fig 1. Some examples of Traffic Signs on road.

2. RELATED WORK

A significant number of papers that deal with the recognition of ideogram-based road signs in real road scenes have been published. The most common approach, quite sensibly, consists of two main stages: detection and recognition. The detection stage identifies the regions of interest and is mostly performed using color segmentation, followed by some form of shape recognition. Detected candidates are then either identified or rejected during the recognition stage using, for example, template matching or some form of classifier such as SVMs or neural networks. The majority of systems make use of colour information as a method for segmenting the image. The performance of colour-based road sign detection is often reduced in scenes with strong illumination, poor lighting, or adverse weather conditions such as fog. Colour models, such as hue– saturation–value (HSV), YUV, and CIECAM97, have been used in an attempt to overcome these issues. For example, Shadeed et al. performed segmentation by applying the U and V chrominance channels of the YUV space, with U being positive and V being negative for red colours. This information was used in combination with the hue channel of the HSV color space to segment red road signs. Gao et al. applied a quad-tree histogram method to segment the image based on the hue and chroma values of the CIECAM97 color model. Malik et al. thresholded the hue channel of the HSV color space to segment red road signs. In contrast, there are several approaches that entirely ignore color information and instead use only shape information from grayscale images. For example, Loy and Zelinksy proposed a system that used local radial symmetry to highlight points of interest in each image and detect octagonal, square, and triangular road signs. Some recent methods such as and use HOG features for road sign feature extraction. Creusen et al. extended the HOG algorithm to incorporate color information using the CIELAB and YCbCr color spaces. Overett et al. presented two variant formulations of HOG features for the detection of speed signs in New Zealand. We also use HOG features to aid our classification process and will explain later why we find they are most suited to this application. The vast majority of existing systems consist of classifiers that were trained using hand-labeled real images, which is a repetitive, time-consuming, and error-prone process. Our method avoids collecting and manually labeling training data, because it requires only synthetic graphical representations of signs that were obtained from an online road sign database. Furthermore, although many existing systems report high classification rates, the total number of traffic sign classes recognized is generally very limited, and are hence less likely to suffer mismatches against similar signs that were missing from their databases. Our proposed system uses all instances of ideogram-based traffic symbols used and hence performs its matching in this larger set. We expect our approach to be equally functional if applied to other country’s traffic sign databases obtained in a similar fashion. Note that many proposed systems suffer from slow speed, making them inappropriate for application to realtime problems. Some methods reports processing times of

Fig 2. Example of an Ideal Traffic Sign detection system

3. TRAFFIC SIGN DETECTION AND RECOGNITION

The proposed system consists of the following two main stages: detection and recognition. The complete set of road signs used in our training data and recognized by the system. The system uses the Raspberry Pi as the processing engine and OpenCV as the software engine. The detection stage uses the 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. (Just imagine how much computation it needs?

Even a 24x24 window results over 160000 features). For each feature calculation, we need to find sum of pixels under white and black rectangles. The first feature selected seems to focus on the property that the region of the sign is often darker than the region inside. All the desired features are written to the file which is then loaded at runtime. The recognition stage is used to confirm a candidate region as a traffic sign and classify the exact type of sign. For the classification of candidate regions, their HOG features are extracted from the image, which represent the

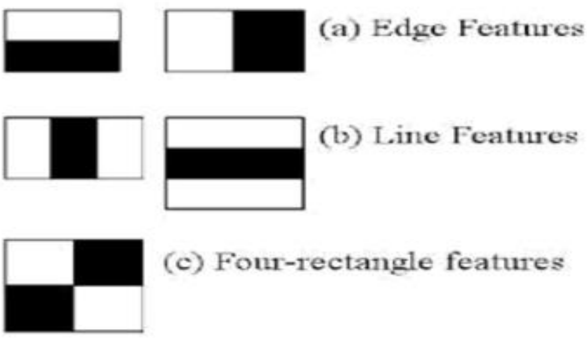

Fig 3. Desired features in an image.

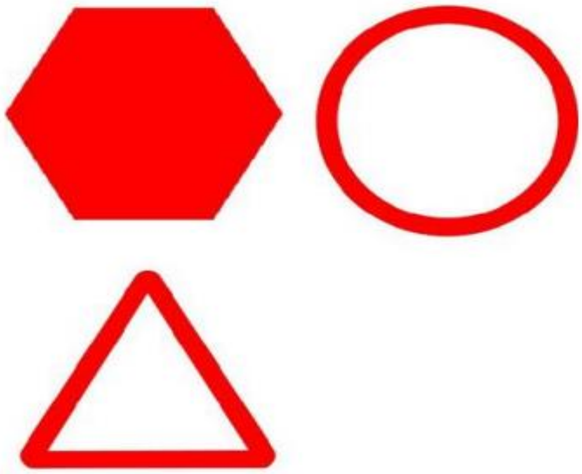

Fig 4. Examples of images used for training the cascade

occurrence of gradient orientations in the image. HOG feature vectors are calculated for each candidate region. A Sobel filter is used to find the horizontal and vertical derivatives and, hence, the magnitude and orientation for each pixel. We find the application of HOG to recognition of traffic symbols very suitable, given that traffic symbols are composed of strong geometric shapes and high-contrast edges that encompass a range of orientations. Traffic signs are generally found to be approximately upright and facing the camera, which limits rotational and geometric distortion, removing the need for rotation invariance. The HOG features are computed on a dense grid of cells using local contrast normalization on overlapping blocks. A nine-bin histogram of unsigned pixel orientations weighted by magnitude is created for each cell. These histograms are normalized over each overlapping block. The components of the feature vector are the values from the histogram of each normalized cell. Regions are then classified using a cascade of multiclass SVMs. SVM is a supervised learning method that constructs a hyper plane to separate data into classes. The "support vectors" are data points that define the maximum margin of the hyper plane. Although SVM is primarily a binary classifier, multiclass classification can be achieved by training many one against one binary SVMs. SVM classification is fast, highly accurate, and less prone to over fitting compared to many other classification methods. It is also possible to very quickly train an SVM classifier, which significantly helps in our proposed method, given our large amount of training data and high number of classes. However, we plan to perform further comparison with other classification methods in future work. Each region in our system is classified using a cascade of SVM classifiers. First, the candidate region is resized to 24 × 24 pixels. A HOG feature vector with 144 dimensions is then calculated, and this feature vector is used to classify the shape of the region as a circle, triangle, upside-down triangle, rectangle, or background. Octagonal stop signs are considered to be circles. If the region is found to be background, it is rejected. If the region is found to be a shape, it is then passed on to a (symbol) sub classifier for that specific shape. We have proposed a novel real-time system for the automatic detection and recognition of traffic symbols. Candidate regions are detected as Haar cascades. This detection method is significantly insensitive to variations in illumination and lighting conditions. Traffic symbols are recognized using HOG features and a cascade of linear SVM classifiers. A method for the synthetic generation of training data has been proposed, which allows large data sets to be generated from template images, removing the need for hand labeled data sets.

4. ADVANTAGES OF THE SYSTEM

The system uses the Viola-Jones algorithm to detect signs, which is a very fast and accurate algorithm if trained properly. This enables the detection on embedded devices possible where low computing power is available. Also the system uses the HOG algorithm to extract features to train the SVM cascade, which is again very accurate. The features extracted are then fed to SVM cascade instead of other algorithms like ANN, KNN which are not as accurate as the SVM algorithm. Moreover, SVM does not have a K value like KNN, which slows it as the value increases.

5. REFERENCES

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