CS6476 Computer Vision Spring 2018 Final Project

Topic: Enhanced Road Sign Detection

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Video presentation:

https://drive.google.com/file/d/1BU8edto8uIQDMjmOidsHZRs2Idg9NetU/view?usp=sharing

Summary

In this report I have implemented an algorithm to detect and classify traffic signs and traffic lights in real world images. The traffic signs include "Stop", "Do not enter", "Yield", "Warning" and "Construction". Red and green traffic lights can be detected and distinguished. The detection algorithm works well with challenging conditions including adverse lightning, partial occlusions and difficult weather. Due to the scope of this project, the classification of different signs within the "Warning" category such as "Merge", "Pedestrian" and "Signal Ahead", and the detection of other traffic signs such as "Speed limit" are not implemented. The algorithm was tested against a subset of images from the LISA traffic sign dataset [1] and the CURE-TSD dataset [2-3] with detection rates ranging from 35% to 92% under no challenge or controlled challenge conditions.

Introduction

Existing road sign detection methods published in recent research

The detection and recognition of traffic signs has been a topic of computer vision research for a decade, as a robust, real-time traffic sign detection algorithm is essential for developing driving aid systems or self-driving vehicles. The existing methods in current research often take three steps composed of detection, classification and recognition.

Sign detection is the process of isolating regions of interest (ROI) that potentially contain traffic signs. Color segmentation in the HSV color space is a commonly used method but other color spaces such as LAB has also been used [4-10]. Classification is the stage of classifying signs into different categories such as warning, prohibition or information based on geometric and color features. Some studies took advantage of edge and corner detection [4, 5], whereas others evaluated matching to different shapes [6][7]. A few signs can be identified at this stage based on their unique shapes including triangles or octagons. Finally, the recognition process determines the identity of the sign, which can be implemented by extracting the pictogram and curvature scale space (CSS) representation [8], by template matching with an extra tracking stage [6], and the most popular methods are different machine learning algorithms implementing softmax [3], support vector machine (SVMs) [9] or neural network classifiers [5, 10].

Methods

The traffic detection method described in this report detects traffic lights and five different traffic signs as shown in Figure1.

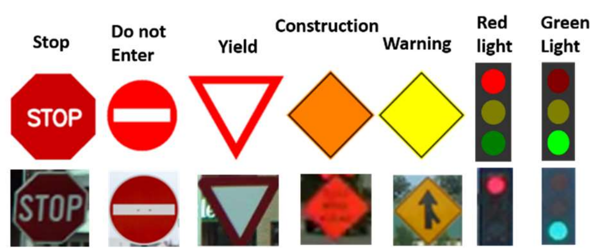

Figure1. Types of signs that can be detected by the method

Method overview

The algorithm follows the steps below (Step 1-4 for detection and 5-6 for classification) and is illustrated using the example of "Stop" sign in the flow chart shown in Figure 2.

1. Create a binary image by applying color masks to the original image in the HSV color space. Use red mask for stop, yield and do not enter signs, yellow mask for warning signs, orange mask for construction signs, green mask for green traffic light and red mask for red traffic light (parameters of saturation and value are different from those set for red road signs).
2. Identify red contours of size above a threshold (cv2.findContours) using the binary image.
3. Identify the bounding rectangles of these contours (with thresholds set for white pixel percentage and ratio of the rectangle shape).
4. Isolate squares from the binary image (or a rectangle of height/width ratio of 3 for traffic lights) as ROI (region of interest) based on the bounding rectangles.
5. Compare the isolated ROI with templates of different traffic lights and traffic signs and return a value of similarity (using the cv2.matchTemplate function).
6. Compare values of correlation coefficient from matching with different sign types. Set thresholds to assign a ROI to a specific sign type.
7. Return the positions and the sign type label of all positive ROIs in an image.

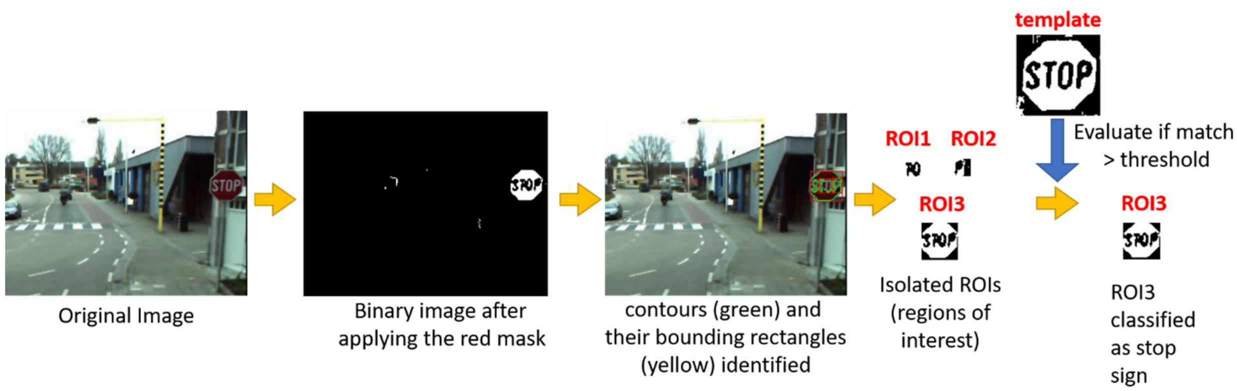

Figure2. Flowchart of the detection method (using "Stop" Sign as an example)

Results

Positive examples and analysis

As shown in Figure3 and Figure4, the road sign method is able to perform the following functions:

1. Detect and classify five different traffic signs and two different traffic lights
2. Work on different instances of traffic signs and lights
3. Detect different types of warning signs (pedestrian, signal ahead and merge) without identifying the exact type
4. Detect and classify multiple traffic signs and lights contained in the same image
5. Work for small traffic signs and lights from a distance
6. Work for partially occluded traffic signs and lights
7. Work for images with difficult weather conditions (using snow as an example)
8. Work for images with adverse lighting

The HSV color space allows the separation of color and intensity information, which helps the algorithm to work under difficult weather and adverse lighting conditions. The ROI detection step in the method reported here works very effectively, attributed to the careful setting of the thresholds to generate different color masks. For tuning the HSV parameters, this website [11] is very helpful. Moreover, when matching the ROI and the sign template, ROI was used as the "template" and the template was treated as the image to be scanned, and this improves the detection of partially occluded signs.

Figure3. Examples of road sign ("Stop", "Do not enter" and "Yield") detection under conditions of different challenging levels

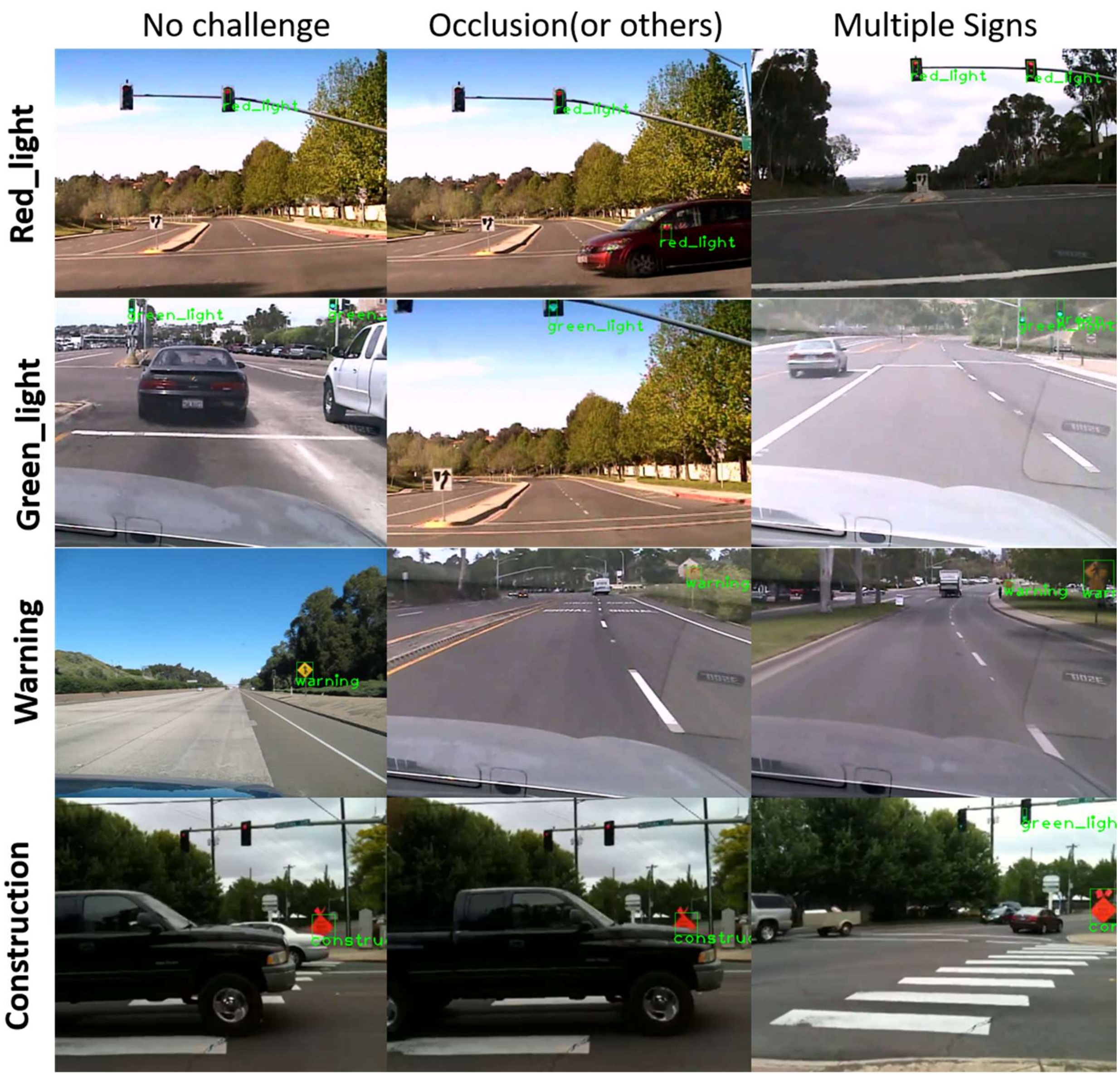

Figure4. Examples of warning and construction sign

Negative examples and analysis

As shown in Figure5, this method has a high failing rate under the following conditions:

1. The stop sign and red light detection has a high false positive rate for brake lights on vehicles
2. The stop sign detection has a high false positive rate for construction signs
3. Does not work effectively for very small traffic lights and signs
4. Does not work effectively for extreme weather conditions (especially the rain)
5. Does not work for gray images that contain no color information
6. Cannot interpret textual information and distinguish between different warning signs

Most road signs in the CURE-TSD and LISA databases are very small, therefore, to achieve a high detection rate, a low threshold is set for sign detection, and a higher threshold significantly reduces the false positive detections. Break lights on cars resemble red traffic light, especially on a black vehicle, resulting in false positives. Also, the separation of red and orange color is not very clean, because red and orange have very close H values. As a result construction sign is sometimes classified as a stop sign.

Figure5. Examples of false negatives and false positives

Statistics Analysis

The CURE-TSD dataset was used for generating statistics data for stop signs, do not enter signs and yield signs (Table 1). A nice feature of this dataset is that it contains images of difficult weather and adverse lighting conditions. However, the CURE database is about European road signs and did not contain US warning signs, construction signs and there are very limited numbers of images containing traffic lights. As a result, the LISA dataset was used for these 3 types of signs (Table 2).

Table 1. Statistics analysis on Stop, Do Not Enter and Yield using the CURE-TSD dataset.

		“Stop”	“Do Not Enter” **	“Yield”
No Challenge	Detection rate*	74.5% (55 frames)	42.3% (26 frames)	75.6% (86 frames)
	False positives	3.2% (600 frames)	1.3% (600 frames)	1.2% (600 frames)
	Video name	01_04_00_00_00 01_45_00_00_00	01_32_00_00_00 01_39_00_00_00	01_08_00_00_00 01_37_00_00_00
Difficult weather (snow)	Detection rate*	69.1% (55 frames)	34.6% (26 frames)	65.1% (26 frames)
	False positives	6% (600 frames)	1.3% (600 frames)	1.2% (600 frames)
	Video name	01_04_01_11_02 01_45_01_11_02	01_32_01_11_02 01_39_01_11_02	01_08_01_11_02 01_37_01_11_02
Darkening	Detection rate*	61.8% (55 frames)	38.5% (26 frames)	72.1% (26 frames)
	False positives	3.1% (600 frames)	1% (600 frames)	3% (600 frames)
	Video name	01_04_01_04_02 01_45_01_04_02	01_32_01_04_02 01_39_01_04_02	01_08_01_04_02 01_37_01_04_02

*Detection rate is defined as the percentage of signs that are detected and classified correctly.

** The detection rates of the “Do not enter” sign is rather low compared to the other 2 signs, and this is probably caused by the fact the CURE-TSD dataset has a very limited number of images that contain “Do not enter” signs, and the signs in these images are very small.

Table 2. Statistics analysis on traffic lights, Warning and Construction signs using the LISA dataset.

	Red Light	Green light	Construction*	Warning
Detection rate	84.8% (46 frames)	91.9% (37 frames)	70% (10 frames)	70.3% (37 frames)
False positive	6.1% (114 frames)	0% (114 frames)	1.8% (114 frames)	6.1% (114 frames)

*The LISA dataset does not contain construction signs, and the 10 positive images were generated from a video on Youtube [12].

Discussion

Comparison to the state-of-the-art methods

The detection rates of this reported method are lower (except for green light at around 92%) compared to state-of-the-art methods, especially considering that only a limited number of signs were included, a relatively small collection of input images was used, and the warning signs are only classified but not identified. In the CURE-TSD paper, the accuracy using different methods (softmax, SVM or NN combined with grayscale, RGB or HOG baseline) range from 80% to near 100% under no challenge conditions, and at the challenge level of "02", which means mild-middle challenge and was used in this report, the accuracy drops to 70%-90% for snow (code 11) and 70% - 90% for darkening (code 04) [3].

Proposals on improving the method.

The detection process of the implemented algorithms worked effectively. However, the parameters need further tuning to better separate the orange and red colors. The size information should be taken into consideration with threshold values set to get rid of the false positives, which are often generated from small, irrelevant areas such as red break lights. The classification process can be improved by using multiple template images of the same sign type, by better tuning the threshold values, or by using a machine learning algorithm instead of template matching. One such algorithm is object detection by HOG (histograms of oriented gradients) combined with a linear Support Vector Machine (SVM) algorithm [9].

References

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