Traffic Sign Recognition Based on HOG Feature and SVM

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Introduction

Problem: Reliable identification of road traffic signs

Relevant applications

Autonomous Driving

Image-based traffic sign recognition is essential for safe and reliable assisted driving and autonomous driving vehicles.

Street-View Integration

Detecting signs from images lets us integrate them into map/street-view platforms (e.g., Google Maps) to improve navigation and situational awareness.

Introduction - Pipeline Flow

1. Image enhancement
2. Color segmentation
3. Sign localization
4. HOG Feature extraction
5. SVM classification

- Boost contrast and normalize lighting (RGB→YUV + adaptive histogram equalization) for clearer sign appearance.
- Convert to HSV and threshold hue ranges to isolate red/blue/yellow candidate regions.
- Find sign candidates with Hough circle detection and contour/polygon analysis (tri/quad detection).
- Compute gradient-orientation histograms on normalized patches (e.g., 64×64, 8×8 cells) to form robust descriptors.
- Train an SVM to classify HOG vectors into traffic-sign categories.

Prior Work

Extensive research has been conducted on **traffic sign detection** using **Deep Convolutional Neural Networks (CNNs)** and **Support Vector Machines (SVMs)**.

Greenhalgh et al. (2012) — German Traffic Sign Detection

Proposed a two-step method:

1. **MSER (Maximally Stable Extremal Regions)**
   Extracted **candidate areas** of traffic signs by identifying stable regions in varying illumination and contrast.
2. **SVM Classifier with HOG Features**
   Trained on features extracted from these candidate regions for precise classification.

This approach achieved **high accuracy** on the **GTSRB (German Traffic Sign Recognition Benchmark) dataset**, proving the effectiveness of combining **MSER + HOG + SVM**.

Prior Work

Rise of Deep Learning

With the rise of **Deep Learning**, researchers adopted **Deep Neural Networks (DNNs)** for **end-to-end recognition**.

DNN-based models automatically learn both **feature extraction and classification**, eliminating manual feature design.

Deep CNN Architectures

German scientists trained **deep CNN architectures** for traffic sign recognition, achieving:

- **Accuracy surpassing average human recognition levels**.
- Improved robustness under **lighting, rotation, and occlusion** conditions.

These advancements laid the foundation for **modern intelligent driving systems**.

But what is different?

The difference lies in the pre-computation part of the pipeline.

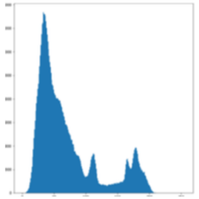
01 IMAGE ENHANCEMENT

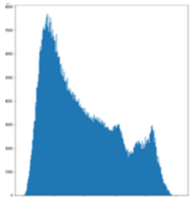
Transform camera image to YUV using equations below and then applying adaptive histogram equalisation:

Y = 0.299R + 0.587G + 0.114B

U = −0.147R − 0.289G + 0.436B

V = 0.615R − 0.515G − 0.100B





02 COLOR SEGMENTATION

Transform into HSV values and segment based on the commonly used colours in traffic signs(red, yellow, blue).

$$V = \frac{(R+G+B)}{\sqrt{3}} \qquad H = \begin{cases} \theta, B \le G \\ 360° - \theta, B \ge G \end{cases}$$

$$S = 1 - \frac{\sqrt{3}}{V}\min(R, G, B) \qquad \theta = \arccos\left[\frac{(R-G)+(R-B)}{2\sqrt{(R-G)^2+(R-B)(G-B)}}\right]$$

03 SIGN LOCALISATION

- Circle detection: Use the Hough transform to map edge points into parameter space and detect circles robustly
- Triangle/rectangle detection: Extract contours from the binary image, apply polygonal fitting to remove noise, then classify shapes by vertex count (3 → triangle, 4 → rectangle).

HOG Extraction

HOG is a feature descriptor commonly used for target detection in computer vision and image processing. It can well represent the outline and edge information of traffic signs.

The gradient of the traffic sign image in the horizontal and vertical directions of the pixel points (x, y) is:-

$$G_x(x,y) = I(x+1,y) - I(x-1,y)$$
$$G_y(x,y) = I(x,y+1) - I(x,y-1)$$

Horizontal and Vertical Gradients

$$G(x,y) = \sqrt{G_x(x,y)^2 + G_y(x,y)^2}$$

Magitude

$$a(x,y) = \arctan\left(\frac{G_y(x,y)}{G_x(x,y)}\right)$$

Direction

- Divide the image into several cells
- Collect the gradient direction histogram of each pixel point in each cell
- Cells are blocked and normalized
- Feature vectors in all the blocks are concatenated

$$N = \left(\frac{I_w}{C_w} - 1\right) \times \left(\frac{I_h}{C_h} - 1\right) \times B \times H$$

- N = Dimension of HOG feature space
- Iw and Ih = dimensions of image
- Cw and Ch = dimensions of cell
- B = number of cell in each block

SVM Training, Evaluation & Conclusion

SVM Formulation

Map HOG descriptors to a high-dimensional space via kernel methods; training minimises $||\omega||^2/2 + C\sum\varepsilon_i$ to obtain maximum-margin hyperplane.

Hyperparameters & Kernel

Select penalty **C (from 1 to 200)** and **kernel (Linear, Polynomial, RBF, Sigmoid)** to produce optimal trade-off between margin and misclassification.

Validation & Results

Evaluate on the test set and additional sample subsets — model demonstrates robustness under varying illumination and partial occlusion; failure modes include very small targets, severe reflections, and strong motion blur.

Conclusion

HOG + SVM provides a computationally efficient and accurate baseline for traffic sign recognition; remaining challenges motivate future work on small-object detection and blur/reflection mitigation.

GTSRB — German Traffic Sign Recognition Benchmark

1

Overview

Real-world traffic-sign dataset for classification and detection.

2

Scale & Classes

≈ **50k images**, **43 classes** (multi-condition imaging).

3

Image & Format

PPM images, variable sizes (~15×15 to 250×250); each image contains one sign.

4

Annotations

CSV files per class with image size, bounding-box (ROI) coordinates and ClassId.

What We Will Demonstrate.

1. **Preprocessing & Enhancement**: Implement RGB→YUV conversion and adaptive histogram equalisation on the Y channel to correct blur/brightness.
2. **Colour Segmentation:** HSV/H-based thresholding to extract red/blue/yellow candidate regions.
3. **Localisation & Shape Analysis(Using OpenCV Python Library):** Detect circular signs via Hough transform and polygonal signs via contour + polygon approximation.
4. **Feature Extraction:** Compute HOG descriptors on resized sign patches (64×64) to form feature vectors for classification.
5. **Classifier Implementation**: Train an SVM on a subset of the GTSRB dataset, but produce the final model using the scikit-learn Python library using the whole dataset.
6. **Evaluation & Analysis**: Report accuracy, per-class recall/precision and confusion matrix using scikit-learn Python library.