

Construction of Cascaded Traffic Sign Detector Using Generative Learning

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Abstract

We propose a method for construction of a cascaded traffic sign detector. Viola et al. have proposed a robust and extremely rapid object detection method based on a boosted cascade of simple feature classifiers. To obtain a high detection accuracy in real environment, it is necessary to train the classifier with a set of learning images which contain various appearances of detection targets. However, collecting the traffic sign images manually for training takes much cost. Therefore, we use a generative learning method for constructing the traffic sign detector. In this paper, shape, texture and color changes are considered in the generative learning. By this method, the performance of the traffic sign detection improves and the cost of collecting the training images is reduced at the same time. Experimental results using car-mounted camera images showed the effectiveness of the proposed method.

1. Introduction

In recent years, the demand for techniques for supporting safe driving has been on the rise. In this paper, we focus on the task of traffic sign detection and recognition with a car-mounted camera. A high-accuracy traffic sign recognition technique can increase driving safety. For instance, it can provide a driver with warnings such as “over speed limit” or “no passing” based on the signs.

Regarding traffic sign recognition, the detection process plays a particularly important role. The majority of existing traffic sign detection approaches makes use of color features [1] and shape features [2]. We utilize a cascaded classifier proposed by Viola et al. [3] (hereafter called “classifier-cascade”). Fig. 1 shows that the classifier-cascade combines multiple classifiers successively in a cascade struc-

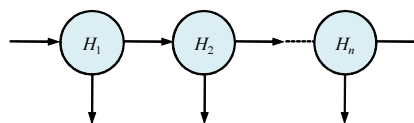


Figure 1. Architecture of a classifier-cascade.

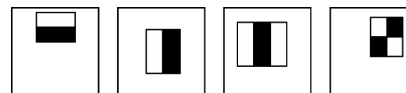


Figure 2. Examples of Haar-like features.

ture, where each of them consists of a combination of weak classifiers that are selected by the AdaBoost algorithm. Due to the evaluation of local edge features using the Haar-like features (Fig. 2), robust and real-time object detection in various lighting conditions is achieved. The classifier-cascade is widely used for face detection, and recently has also been applied to traffic sign detection [4].

For stable and high detection performance, however, it is necessary to construct a classifier using learning images that include various possible appearances of traffic signs appropriately. Since traffic signs are situated in various environments, shape, texture and color changes appear in camera-captured images. Examples of these changes are shown in Fig. 3. In general, it is difficult to collect a massive number of traffic sign images which contain various appearances as learning data. For example, there are significant difference in colors of each captured traffic sign image because of discoloration, reflection and shadow. Collecting traffic sign images including such appearances is very hard.

To cope with this problem, in this paper, we propose a method for constructing a cascaded traffic sign detector using a generative learning method [5] considering shape, texture and color variation.



Figure 3. Examples of Japanese traffic signs captured in various conditions. These captured images contain various changes on shape, texture and color, such as 3D-rotation, stretching, optical blurring, background pattern, discoloration and reflection.

2. Construction of cascaded traffic sign detector using generative learning

We propose a method for constructing a traffic sign detector using a generative learning. The generative learning is a learning method with a massive number of generated training samples which contain various appearances. Firstly, we define seven generation models on shape, texture, and color changes. Secondly, we prepare a few original traffic sign images as generation sources. Thirdly, we generate artificial traffic sign images from the original images with the models. Then, we obtain a massive number of generated traffic sign images for learning. By this method, the cost of collecting traffic sign images is greatly reduced.

2.1. Modeling shape, texture and color changes

We define the following seven models to generate traffic sign images for learning.

- **Shape and texture change models**

Rotation : This is simulated by adding a rotation around each axis θ_x , θ_y , θ_z of 3D-coordinates with the origin set at the center of the original image.

Shifting : This is simulated by adding a horizontal shifting Δx and a vertical shifting Δy to the original image.

Stretching : This is simulated by expanding the width of the original image r_w times, and its height r_h times.

Optical blurring : This is simulated by calculating the convolution of the original image and the following

Gaussian function:

$$h(x, y) = \frac{1}{2\pi\sigma} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \quad (1)$$

where the parameter σ controls the degree of optical blurring.

Background pattern : This is simulated by extracting several background patterns from some camera-captured images, and combine them with input images.

- **Color change models**

Discoloration : The resistance to discoloration depends on color. Thus we divide the original image to n color regions. Then, we determine color (h_i, s_i, v_i) of each region i by adding color variation in HSV color space. As a result, we can get obtain a discolored image composed by n color regions.

Reflection and shadow : In this paper, we assume that the brightness changes uniformly in a captured image, so the impact of a partial shadow or a specular reflection are not considered. Changes of hue and saturation caused by lighting conditions, such as sunset, are not considered as well. To simulate the reflection and the shadow, a brightness variation v is added to all pixels of the original image.

2.2. Generation of traffic sign images

The degree of changes contained in each generated traffic sign image is controlled by a parameter vector $\mathbf{P} = (\theta_x, \theta_y, \theta_z, \Delta x, \Delta y, w, h, \sigma, n_b, h_i, s_i, v_i, v)$. Traffic sign images containing various appearances are generated by selecting various parameter vectors appropriately. Fig. 4 shows examples of the generated traffic sign images.

2.3. Construction of a cascaded traffic sign detector

To construct a traffic sign detector, we train a classifier-cascade with the traffic sign images generated by the above method. Each stage of the classifier-cascade is trained based on the AdaBoost algorithm, and Haar-like features are selected by evaluating the feature values in the following seven color representation [4]. This enables us to make beneficial use of color features in the traffic sign detection process.

- $R \ G \ B$
- $r = R/S \ g = G/S \ b = B/S \ (S = R + G + B)$
- $Grayscale = 0.2989R + 0.5866G + 0.1145B$



Figure 4. Examples of the generated traffic sign images. In the experiments, detection targets are these twenty kinds of round regulatory signs.

3. Experiments

3.1. Conditions

In the following experiments, video data captured by a car-mounted camera in various conditions were used as a test set. A total of 6,874 frames (resolution : 640×480 pixels) which include 12,235 target signs whose diameter is 15 – 45 pixels were in the test set. For the learning of a classifier-cascade for traffic sign detection, a total of 5,000 traffic sign images were generated from one computer-graphic image for each category. We assume that each generation parameter is controlled by a normal distribution, whose mean μ and standard deviation σ are shown in Table 1. Regarding the discoloration model, we segmented each original image by color, though discoloration was applied only to the red and the blue regions. For the background-pattern model, background patterns for integrating a traffic sign image were selected from 215 scenery images at random.

3.2. Methods

In order to evaluate the effectiveness of the proposed method, we investigated the detection performance of two

sets of classifiers, both using generative learning, but one considering shape, texture and color variations and the other considering only shape and texture variations. In addition, both experiments were performed under two different image representation conditions; one using only *Grayscale* (gray feature), and the other using $R, G, B, r, g, b, Grayscale$ (color feature). In total, we investigated the performances of four sets of classifier-cascades constructed by the proposed method under the following conditions.

1. Generation without color variation, and then learning gray feature.
2. Generation without color variation, and then learning color feature.
3. Generation with color variation, and then learning gray feature.
4. Generation with color variation, and then learning color feature.

3.3. Results

In the case of generation with color variation and learning with seven color representation, the best performance, precision = 0.97 and recall = 0.95, was obtained. The results obtained by the other classifier-cascade are shown in Table 2. Provided that the center point of a target sign was inside the detected window, it was counted as a correct result.

These results show that the performance of the classifier-cascades constructed by generative learning considering color variation are higher than those of the others. This could be interpreted as that the detector was more robust to color variation since it was constructed by the generative learning considering color variation as well as shape and texture variation. Learning a classifier based on the images, including various possible color variations, leads to the stable detection of these images.

Moreover, which of considering color variation in generative learning, the effect of performing under seven color representation was different. Unless a classifier is constructed with learning images which contain possible color variations, the color feature selected in the learning process may not be effective. This explains the reason that the detection performance was high when considering color variation and representing the image with seven colors, but was low when color variation was not considered.

Fig. 5 illustrates the examples of the detection results by the proposed method.

4. Conclusion

We proposed a method for traffic sign detection with a classifier-cascade based on a generative learning. The generative learning method took account of several factors of

Table 1. Mean and standard deviation of generation parameters.

	Shape and texture models								Color models						
	Rotation [°]			Shifting [pixels]		Stretching		Optical blurring	Discoloration						Reflection & shadow
	θ_x	θ_y	θ_z	Δx	Δy	w	h	σ	Red region			Blue region			
μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
μ	0.0	0.0	0.0	0.0	0.0	1.0	1.0	0.0	355.0	0.65	0.8	214.0	0.7	0.7	-0.25
σ	2.45	2.45	2.45	10.0	10.0	0.078	0.078	2.0	9.49	0.14	0.045	7.75	0.16	0.045	0.17

Table 2. Comparison of detection ability.

Generation	without color variation		with color variation	
	gray feature	color feature	gray feature	color feature
Precision	0.85	0.96	0.85	0.97
Recall	0.74	0.56	0.85	0.93
F-measure	0.79	0.71	0.85	0.95

color changes such as discoloration, reflection and shadow, as well as the factors of shape and texture changes. It enabled us to simulate the actual changes of a camera-captured image. In addition, both gray edge feature and color edge feature have been effectively used by the classifier-cascade based on generative learning. The experiments showed the effectiveness of the proposed method by evaluating the detection performance of the classifiers.

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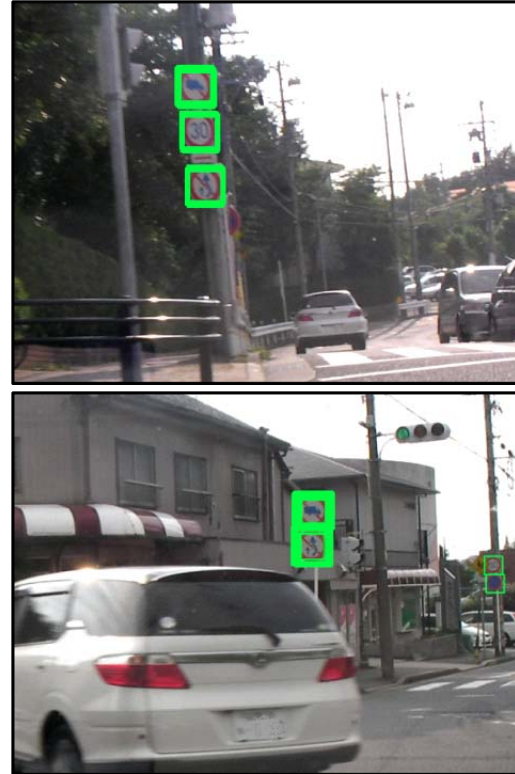


Figure 5. Examples of the detection results. Each rectangle represents detected traffic sign.

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