Traffic sign change detection based on grayscale adaptive SVM

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Abstract: The use of vehicle image detection to detect traffic information along roads is a key technology for high-precision navigation map updating. At present, China’s roads are developing rapidly. Traffic signs along the roads are constantly updated as the roads change. An accurate and efficient method for detecting traffic signs along the roads is yet to be proposed. Aiming at this problem, this paper proposes a road traffic signage change detection method based on Grayscale Adaptive SVM (Support Vector Machine). First extract the traffic signs in the two-stage image, rotate and interpolate the operation, automatically rotate the guide card to the horizontal, and zoom to the uniform size, grayscale the image pair and extract the changed part using the SVM model, and finally use the morphological operator. Process images to remove the effects of “salt and pepper” noise. Through experimental verification, this method can detect changing areas accurately and efficiently, eliminate the influence of parallax, and have a higher degree of automation.

1. Introduction
High-precision navigation maps are electronic navigation maps with higher precision and more data dimensions. It contains detailed road models and a large amount of driving assistance information compared to ordinary navigation maps. High-precision navigation maps are the first-hand knowledge of autonomous driving, and the shorter update cycle is the guarantee of high-precision navigation map reliability [1]. However, the development of high-precision navigation maps is constantly facing challenges. At present, China is in a stage of rapid development. The roads are changing with each passing day, and the overall cost of maps is high. It is necessary to detect and update road changes efficiently. Traffic signage is an important part of high-precision navigation maps as a facility for managing traffic and indicating driving directions to ensure smooth roads and driving safety.

Change detection is the process of identifying changes by observing objects or phenomena at different times [2]. The vehicle image is affected by non-human factors such as weather, illumination, and sensors, and nonlinear changes often occur between the acquired pairs of images. Traditional change detection methods such as image difference, image ratio[3] and other simple arithmetic operations, change vector analysis method to construct image differences through multi-band simple arithmetic operations, it is difficult to achieve automatic threshold setting[4]; principal component analysis The method[5] and the multivariate change detection method[6] are difficult to adapt to the nonlinear changes between the changed image pairs. SVM is one of the most effective methods for machine learning in recent years [7], SVM has become a hot spot in change detection research. Li [8] used SVM to detect the urban land change, avoiding the uncertainty of the change threshold. Yue Dong [9] proposed a change detection method combining kernel canonical correlation analysis and SVM.
Implement adaptive determination of the threshold. Yizhi [10] proposed an adaptive multi-feature fusion SVM change detection method, which combines spectral features and texture features, constructs SVM model and extracts changed and unchanged information with PCA (Principal Components Analysis), which is more than general BP neural network. BP neural network can achieve automatic threshold setting, but requires a lot of training data and long training time [11]. Although the above algorithms achieve better results through matching, it is often difficult to achieve automatic matching for large-scale image pairs, and it is affected by illumination conditions and camera viewpoints, and a more efficient and automated change detection method is needed.

As shown in figure 1, the types of road signs along the road are usually divided into four types: road information change signs, type change guides, information increase signs, information-blocked street signs. In this paper, the traffic signboard color is generally the blue and white pattern of the prophetic conditions. The effective area of the traffic sign is extracted by setting the color range, and the interference caused by noise and parallax is reduced by Gaussian blur, interpolation and rotation. And finally get accurate change detection results.

(a) road information change signs  (b) type change guides
(c) information increase signs  (d) information-blocked street signs

Figure 1. Types of traffic signage changes.

2. Methodology

As shown in figure 2. Based on the image adaptive SVM model, the road traffic signage change detection, the pre-processing converts the two-stage image from the RGB color space to the HSV color space at the same time. By setting the color value range, identifying and extracting the pixel area of the traffic signpost will be obtained. The signpost logo is rotated to the horizontal, uniform size, and denoised using median filtering. According to the SVM model two classification, the images are divided into two categories: change and no change. The result map of the change of the signpost information is obtained, and the interference noise is removed by the morphological operator to obtain the change detection result.

Figure 2. Change detection flow chart.
2.1 Pretreatment
In the actual image acquisition, there will be uneven illumination. The RGB channel does not reflect the specific color information of the object. The HSV (Hue, Saturation, Value) space can express the brightness, color and vividness of the color very intuitively. More conducive to the contrast of image color. In order to remove the influence of lighting conditions, the RGB color needs to be converted to HSV color. As Equation (1) to Equation (4).

\[
\begin{align*}
H &= \begin{cases} 
0^\circ, & \text{if } \text{max} = \text{min} \\
60^\circ \times \frac{g - b}{\text{max} - \text{min}} + 0^\circ, & \text{if } \text{max} = r \text{ and } g \geq b \\
60^\circ \times \frac{g - b}{\text{max} - \text{min}} + 360^\circ, & \text{if } \text{max} = r \text{ and } g < b \\
60^\circ \times \frac{b - r}{\text{max} - \text{min}} + 120^\circ, & \text{if } \text{max} = g \\
60^\circ \times \frac{r - g}{\text{max} - \text{min}} + 240^\circ, & \text{if } \text{max} = b \\
0, & \text{if } \text{max} = 0
\end{cases} \\
S &= \frac{\text{max} - \text{min}}{\text{max}}, \quad \text{otherwise} \\
V &= \text{max}
\end{align*}
\]

(1)

(2)

(3)

(4)

Where \(R\), \(G\), and \(B\) are the colors of the three channels of red, green, and blue, respectively. \(H\) represents the hue; \(S\) is the saturation, indicating the degree to which the color is close to the spectral color; and \(V\) is the degree to which the color is bright.

2.2 Traffic sign recognition and extraction
Based on the characteristics of the blue sign and the white pattern of the road sign, the image pixel color range is set to \((100, 43, 46) \sim (124, 255, 255)\) in pixels, and the blue traffic sign area is extracted to generate the mask \(M\). The mask \(M\) is a binary image, white represents the identified signpost information, and black is the other uninteresting parts. However, the actual scene graph has many color interferences, and the image needs to be blurred to remove the noise point interference to the result. Image Gaussian Blur as equation (5):

\[
G(u, v) = \frac{1}{2\pi\sigma^2} e^{-\left(u^2 + v^2\right)/(2\sigma^2)}
\]

(5)

Where \(\sigma\) is the standard deviation of the normal distribution and \((u, v)\) is the coordinate position of the pixel. Gaussian blurring preserves good edge effects [12].

In the actual image, it will be affected by objects with similar colors, such as the influence of blue sky and license plate, and the image taken by different viewpoints has parallax. If there is a false detection, it is necessary to set a reasonable range for the color space and add restrictions. For the extracted false detection target, the road sign area along the road is limited to the non-edge area of the image, and the detected size is within a reasonable range, thereby eliminating the interference factor.

The parallax is generated due to the different shooting angles and positions of the two cameras of the same road sign, and the image is rotated around the center to the horizontal position, as shown in equation (6):
\[ P = \begin{cases} x_1 = x \cos \theta + y \sin \theta \\ y_1 = -x \sin \theta + y \cos \theta \end{cases} \tag{6} \]

Where \( x, y \) is the position of the pixel in the original image, and \( x_1, y_1 \) is the position of the corresponding pixel in the rotated image, \( \theta \) is the angle of rotation. The rotation angle \( \theta \) is calculated from the detected coordinate values of adjacent corner points according to the cotangent formula. Finally, median filtering is used to remove the "salt and pepper" noise.

2.3 SVM model change detection

SVM is a supervised statistical learning method that minimizes empirical errors and maximizes geometric edges, known as the maximum interval classifier. The change information decision is the key and core of the change detection technology, which directly has a decisive influence on the final test result. The decision on the image change area and the invariant area can be approximated as a two-class problem, while SVM has a good processing effect on two-class problem and nonlinear data, and has the ability to identify and extract features in high-dimensional feature space. In this paper, the gray value of the pixels in the image alignment is input to the SVM training model, and the obtained model is used to predict the unknown samples.

For a given data set \( S = \{(x_1, x_2, \ldots, x_l, x), x \in \mathbb{R}^n, y \in \mathbb{R}\} \), where \( l \) is the number of samples, \( x \) is a \( d \)-dimensional vector, and \( y \in \{1, -1\} \) means positive samples and negative samples. For linear separability data, the hyperplane is used to separate the positive and negative classes, and the distance from any point to the plane is greater than or equal to 1, and the hyperplane is as in equation (7).

\[
f(x, a) = w^T X + b \tag{7}
\]

The SVM algorithm uses the principle of structural risk minimization to minimize the generalization function equation (9) under constraint condition equation (8):

\[
\phi(w, \xi^+, \xi^-) = \frac{1}{2} (w \times w) + c \sum_{i=1}^{l} (\xi^+, \xi^-) \\
\begin{cases} 
y_i - (w \times x_i) - b \leq \xi^+ + \epsilon \\
(w \times x_i) + b - y_i \leq \xi^- + \epsilon \\
\xi^+ \geq 0 \\
\xi^- \geq 0 \end{cases} \quad i = 1, 2, \ldots, l \tag{9}
\]

In the formula, \( c \) is the penalty coefficient, which determines a compromise between model complexity and empirical risk error; \( \xi^+, \xi^- \) is the relaxation factor, the tolerance is \( \epsilon \); \( b \) is the offset; \( l \) is the training sample; \( w \) is the weight vector.

According to the Lagrange multiplier method, the problem of seeking the optimal classification hyperplane is transformed into a convex quadratic programming problem. However, the changes between image pairs are not linearly separable. It is necessary to map the two-dimensional data to the high-dimensional space, establish a hyperplane, and realize data classification. It is necessary to introduce a kernel function instead of the inner product in the high-dimensional space. As shown in figure 3, the training is mapped from the low-dimensional space to the high-dimensional space, and the optimal linear separable hyperplane is designed, and the low-dimensional nonlinearity can be divided. The situation translates into a high dimensional linear separability case.
Commonly used kernel functions are linear kernel functions, polynomial kernel functions, radial basis kernel functions (RBF), and Sigmoid kernel functions. As shown in equation (12), \( x_i \) and \( x_j \) is two samples. The radial basis kernel function increases the distribution probability of the original sample features by a Gaussian distribution function. Many experiments have proved that the radial basis kernel function is better than the linear kernel function and the polynomial kernel function, and the parameters are less than the Sigmoid kernel function. The radial basis kernel function is used in this paper.

\[
K(x_i, x_j) = \exp\left(-\frac{P_{x_i} - P_{x_j}}{2\sigma^2}\right)
\]  

(10)

Based on the SVM model, the change of traffic signposts is susceptible to uneven illumination caused by weather changes and camera shooting angles. As a result, the traffic sign image is close to the corresponding pixel color values, which is not conducive to distinguishing and model training. In order to avoid this situation, the specific steps are as follows: (a) graying the change detection image; (b) constructing the difference image and extracting the change detection information using the SVM model of the RBF kernel function; (c) using the influence morphology calculation. The effect of the sub-process classification is to obtain a near-real traffic sign change detection result.

2.4 Morphological processing
According to the obtained difference binary image, the image morphology opening operation, that is, the etching and expansion operation of the image processing is performed. Corrosion is that the highlights in the image are eroded, reducing the area, and the effect map has a smaller highlight area than the original image; dilation is the expansion of the highlights in the image to expand the area. The effect map has a larger highlight area than the original image. Whether it is a corrosion operation or an expansion operation, the image needs to be convolved, and an optimal ratio of the convolution kernel is set to remove the false detection pixels caused by the edge sawtooth pixels and noise interference, and the final change region is obtained.

3. Experiment and result analysis
The experimental data is the vehicle image pairs obtained in two different periods, intercepted in the Baidu map streetscape image, and the shooting time is 2013 and 2015, respectively, and the location is in Beijing. As shown in figure 4. The images acquired at different times have the same size, different shooting positions, different rotation angles of the camera, parallax between the image pairs, and different lighting conditions and road environment.
3.1 Traffic signpost detection and extraction

In the two-stage image, the difference in illumination conditions is the main factor affecting the detection accuracy in the process of identification and extraction of traffic signs. As shown in figure 5. After many experiments, the HSV color value is set in the range of (100, 100, 100) ~ (124, 255, 255). The effect of detecting the signpost is better, the contour of the traffic sign can be accurately detected, and the interference factors such as the sky and the license plate are eliminated.

During the image processing process, the extracted traffic signpost is represented in the mask, and the Gaussian blur removes the noise point to obtain the exact location of the traffic signboard in the original image, and cuts and extracts the traffic signpost in the original image. Set the Gaussian fuzzy convolution kernel to $9 \times 9$ optimal. The traffic signposts are set to a uniform size. The experiment is set to $1296 \times 648$, and the extracted map is finally obtained. The extracted maps cause blurring due to the remote shooting position, and the image color saturation also has some differences. As shown in figure 6.

3.2 Traffic sign change detection

Affected by the parallax and the “salt and pepper” noise when traffic signs are extracted, there will be some sawtooth phenomenon and noise on the information edge of the traffic signboard. Eliminate these effects and perform the image morphology operation on the test results. After many experiments, the convolution kernel of the open operation is set to perform optimally.
Figure 7. Change detection results.

In order to verify the method in this paper, the corresponding test samples are used to conduct corresponding comparison experiments to verify the effectiveness of the image grayscale adaptive SVM model change detection method. As shown in Figure 7.

Table 1. Accuracy statistics

| The standard of evaluation accuracy | Single band SVM | RGB difference SVM | Grayscale adaptive SVM |
|-----------------------------------|----------------|-------------------|------------------------|
| False alarm rate (%)              | 21.99          | 15.49             | 10.98                  |
| Missing alarm rate (%)            | 24.74          | 17.86             | 15.99                  |
| Accuracy rate (%)                 | 89.19          | 92.26             | 93.80                  |
| Time (s)                          | 65.58          | 122.11            | 11.03                  |

The accuracy statistics of each experimental result are shown in Table 1. The single-band SVM detection method has a large false alarm rate, mainly because the single-band is susceptible to illumination, resulting in false detection. The detection effect of the RGB difference SVM model is relatively good, and the illumination condition interference is suppressed under the condition of increasing the input condition, but the judgment factor is increased, resulting in an increase of the calculation time. The performance of the method in this paper has improved in all respects. The use of grayscale reduces the illumination interference while reducing the input conditions, speeding up the calculation, and being able to adapt to the real-time change detection requirements of the road.

4. Conclusion

In this paper, the vehicle image traffic signboards obtained at different times are extracted, and the image is input to the SVM model by the grayscale road sign image, and the change result is predicted. In this paper, by supervising the pixel-level change detection method, the overall process from target extraction to change detection is realized. The target area is accurately determined when the traffic sign image pair cannot be matched, and efficient detection of traffic sign changes along the road. It is proved by experiments that compared to other change detection methods, the method has a better calculation effect, reduces computation time cost and memory management cost, and achieves a higher detection accuracy rate, while reducing illumination and camera acquisition. The influence of interference caused by parallax is feasible in the automatic detection of road traffic signs.
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