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A New Car Seat Detection Method

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Abstract. In order to detect the products of car seat, propose a new car seat detection method in this paper. First, the car seat image is normalized to 256 pixels *256 pixels image. Then extract SIFT (scale invariant feature transform) feature points and match the points. According to the position of two matched points, the matching results are divided into two categories. One is vertical match point; the other is tilt matching point. Compare the number of the two categories. When the vertical match points are more than the tilt matching points, the answer is correct. Otherwise the answer is wrong. Experimental results show that for the detection of three different types of car seats, the detection accuracy is higher than 98%.

Introduction

In recent years, automobile industry has developed rapidly. As a typical product of automobile components, the impact of the optimization of the detection system on the whole automotive parts industry cannot be ignored. For manufacturing enterprises such as car seats, production efficiency and product quality are important benchmarks for the growth and expansion of an enterprise. Therefore, the car seat detection system must meet the efficiency and accuracy of these two elements.

Image feature point detection has been studied for decades. Feature points, also called key points, are defined as pixels with unique features on the image. For example, the intersection of two lines, corners and so on. Most of the feature points cannot be directly observed with the naked eye, because the feature pixels can not only rely on the brightness of the pixel value to decide, such as image gradient, gradient direction is not observed, must pass certain mathematical operations that, in order to determine whether the point is the key point. Harris and corner detection algorithms and Moravec's corner based video image matching algorithm are the early detection methods of feature points. Rosten et al proposed the FAST feature point detection algorithm to detect the feature points by comparing the size of the central pixel and the neighborhood pixel. In addition, there are ORB algorithm, BRISK algorithm, SURF algorithm, PCA-Sift algorithm, and so on. In 1999, Lowe proposed Sift detection algorithm, and improved the algorithm in 2004. Generally speaking, the feature point detection algorithm is a method of image local feature detection and description. It can express the local feature information of the image, so as to realize the expression of the whole image features. For example, the local two valued pattern coding algorithm is also an image local feature expression algorithm, which has been widely used in face recognition. At present, the research of image feature points is still an important research aspect of image processing.

As an image feature point detection algorithm, SIFT algorithm has the characteristics of affine invariance, rotation invariance, and so on. The detected feature points have high stability, able to adapt to complex environments. Therefore, the SIFT algorithm is applied to the detection of the back of the car image, which can realize the detection of components better [1-2].

Image Preprocess

In manufacturing, the position of the cameras and car seats is relatively fixed. Therefore, scaling problems can be ignored in this application. For future SIFT feature matching, normalize the car seat images to 256 pixels *256 pixels by an equal scale method. The normalized effect is shown in Fig. 1.

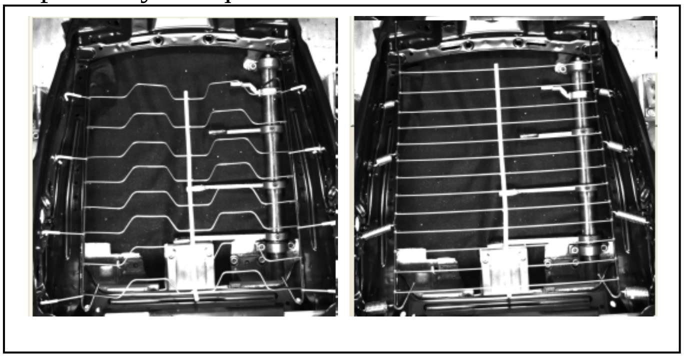


Fig.1 Normalized image of car seats

SIFT Features Extract

The SIFT algorithm uses the image scale space theory to extract the feature points, and has good robustness to image rotation, noise and so on [3].

Generate Scale Space. The Gaussian convolution is the only line core to realize scale transformation. The scale space of a two-dimension image is defined as[4]:

$$L(x,y,\sigma) = G(x,y,\sigma) \times I(x,y) \tag{1}$$

Here, $G(x,y,\sigma)$ is scale invariant Gaussian function. $G(x,y,\sigma) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2}$. (x,y) is the space coordinate. σ is called scale space coordinate.

We need Gaussian difference scale space (DoG).

$$\begin{aligned} &D(x,y,\sigma) \\ &= \big(G(x,y,k\sigma) - G(x,y,\sigma)\big) \times I(x,y) \\ &= L(x,y,k\sigma) - L(x,y,\sigma) \end{aligned} \tag{2}$$

The difference of two adjacent intervals in the Gaussian scale space pyramid creates an interval in the difference of Gaussian pyramid. The construction of scale space could do well with the zooming problem.

Space Extreme Value Point Detection. To search the extreme value point in LoG scale space, each sample point should be compared to its every adjacent point. Every point to be detected should be compared with 26 points to ensure detecting extreme value point in both the scale space and the 2-dimention image space.

Determine the Precise Extreme Value Points. Among the extreme value points which are got from Figure 4, there are a lot of redundancy and unstable points. So it is necessary to do something to determine the precise extreme value points. The most important influence is edge points. So we should remove the edge response. The removing method is as follows.

Introduce Hessian matrix:

$$H = \begin{bmatrix} D_{xx} & D_{xy} \\ D_{xy} & D_{yy} \end{bmatrix} \tag{3}$$

Here

$$\begin{aligned} D_{xx} &= L(x+1,y) - L(x,y) + L(x-1,y) - L(x,y) \\ D_{xy} &= L(x+1,y+1) + L(x-1,y-1) \\ &\quad - L(x-1,y+1) - L(x+1,y-1) \\ D_{yy} &= L(x,y+1) - L(x,y) + L(x,y-1) - L(x,y) \end{aligned} \tag{4}$$

Define

$$\begin{cases} Tr(H) = D_{xx} + D_{yy} \\ Det(H) = D_{xx}D_{yy} - (D_{xy})^2 \end{cases} \quad (5)$$

Suppose α is the maximum eigenvalue, β is the minimum eigenvalue. $\alpha = \gamma\beta$. Then

$$\frac{(\alpha+\beta)^2}{\alpha\beta} = \frac{(\gamma+1)^2}{\gamma} \quad (6)$$

When $\frac{Tr(H)^2}{Det(H)} < \frac{(r+1)^2}{r}$, the corresponding extreme value is chosen by our system.

Distribute the Direction and Generate the Description of Each Feature Points. Distribute the direction for each point using the following formula:

$$\begin{cases} m(x,y) = 2\sqrt{D_x^2 + D_y^2} \\ \theta(x,y) = \operatorname{atan}\frac{2D_y}{D_x} \end{cases} \quad (7)$$

Here

$$\begin{cases} D_x = \frac{L(x+1,y)-L(x-1,y)}{2} \\ D_y = \frac{L(x,y+1)-L(x,y-1)}{2} \end{cases} \quad (8)$$

$m(x,y)$ means the modulus of the vector, and $\theta(x,y)$ means the angle of the vector.

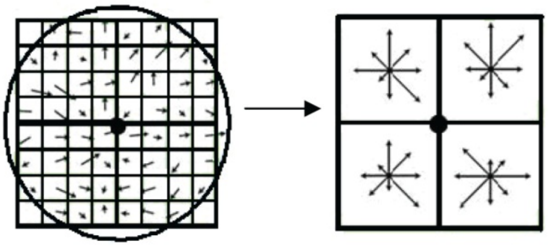


Fig.2 Generate the description of each feature points

Improved SIFT Method

After getting the SIFT features, match the features using traditional SIFT method.

Suppose the coordinate of SIFT feature in first image is (x1,y1),the coordinate of matched point is (x2,y2), calculate the reciprocal of slope of the two points.

$$K=(x2-x1) /(256+y2-y1) \quad (9)$$

When K is less than threshold, this couple of matched points is vertical matched. Otherwise the couple is tilt matched. When vertical matched points are more than tilt matched points, the two car seats are matched. That is the two car seats are the same type.

The flow chart of improved SIFT method is followed as Fig.3.

Experimental Result

To detect the performance of this method, use three different types of car seat to detect. Calculate the vertical match points and tilt match points individually. The detection results are shown in Fig.4 and Fig.5.Group A shows the vertical matching points. Group B shows the tilt matching points.

Fig.4 shows the detection result of three same type car seats. It can be seen from the visual point of view that in Fig.4 vertical matching points are more than tilt matching points. To precisely compare the number of two matching points, calculate the matching points as Table 1. From Table 1, it can be seen that vertical matching points are more than tilt matching points. The detected car seats have same type.

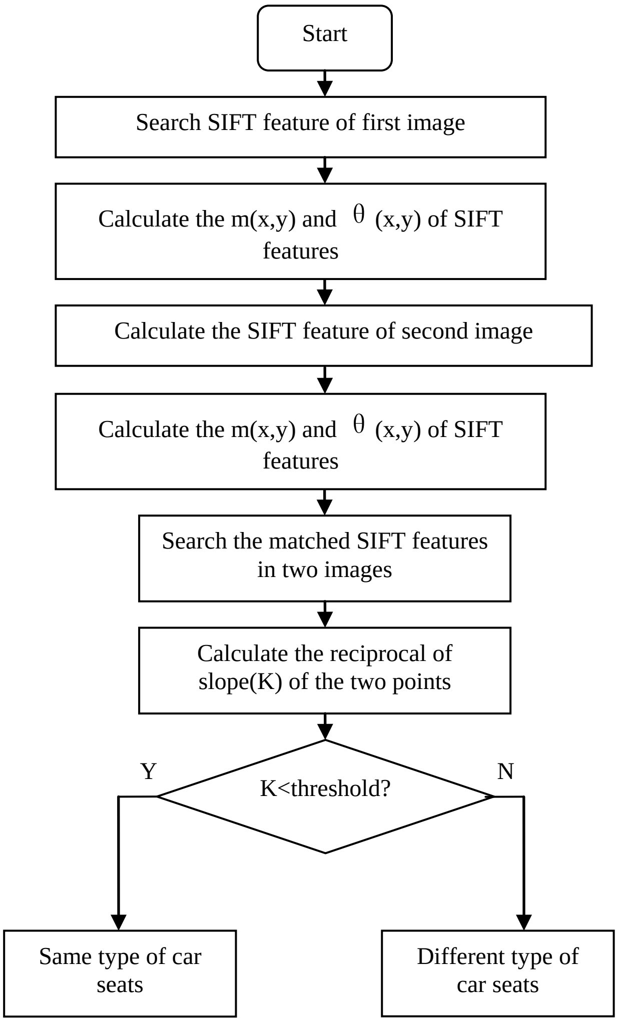
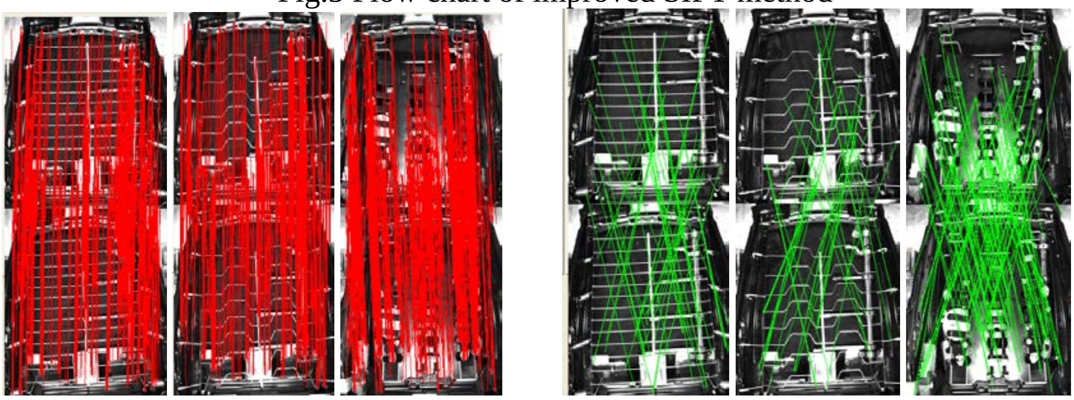


Fig.3 Flow chart of improved SIFT method



a. vertical match points   b. tilt match points

Fig.4 Detection of the same type of seat

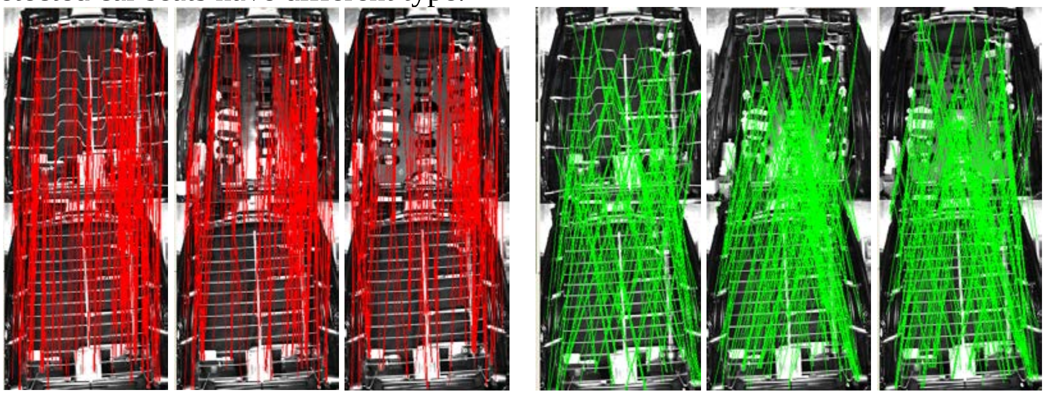
Table.1 Table Type Styles

	Number of matching points		
	Group 1	**Group 2**	**Group 3**
Vertical matching points	137	153	162
Tilt matching points	26	21	34

Fig.5 shows the detection result of three different type car seats. It can be seen from the visual point of view that in Fig.5 vertical matching points are less than tilt matching points.

To precisely compare the number of two matching points, calculate the matching points as Table 2. From Table 2, it can be seen that vertical matching points are less than tilt matching points. The detected car seats have different type.

Conclusion is that when vertical matching points are more than tilt matching points the two detected car seats have the same type. When vertical matching points are less than tilt matching points, the two detected car seats have different type.



a. vertical match points b. tilt match points

Fig.5 Detection of different type of seat

Table.2 Table Type Styles

	Number of matching points		
	Group 1	**Group 2**	**Group 3**
Vertical matching points	83	36	25
Tilt matching points	92	97	95

Summary

This paper proposes a new method to detect the car seat. First, the car seat image is normalized to 256 pixels *256 pixels image. Then extract SIFT feature points and matching. According to the position of two matched points, the matching results are divided into two categories. One is vertical match point; the other is the tilt matching point. Compare the number of the two categories. When the vertical match points are more than the tilt matching points, the answer is correct. Otherwise the answer is wrong. Experimental results show that for the detection of three different car seats, the detection accuracy is higher than 98%. Fully meet the requirements of industrial production.

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