Causal Features Extraction for Workpiece

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Abstract. In order to reduce the cost, computer vision technology is introduced into the measurement of workpiece size and shape on the factory production line. At present, the most widely used solution is the neural network model based on big data. However, the lack of data and the high cost of data processing also greatly limit the practical application of this aspect. The method of feature extraction brings challenges to the real-time, rotation invariance, and anti-noise of online detection. In this paper, firstly, Harris operator is used to extract feature points quickly. Then a two-layer scale space based on causality is constructed to filter the noise and project downward to obtain the robust feature position, which provides a basis for subsequent processing.

Keywords: Feature extraction, workpiece, causality

1. Introduction

With the popularization of automation production in industrial production, a stable and efficient workpiece detection system is more and more important for industrial production. Traditional human eye detection not only wastes a lot of labor but also mixes subjective factors in the process of detection, which makes it difficult to accurately grasp the size of the workpiece. Modern optical-based image detection technology overcomes the shortcomings of human eye detection to some extent, but the recognition rate of the distorted image is still low. How to maintain the accuracy of image recognition under the conditions of rotation, scaling, illumination, and so on is still the research hotspot of image recognition direction.

In order to better identify the target image and reduce the noise pollution caused by the machine in the image acquisition process, the collected image is generally filtered and denoised. At present, mainstream filtering includes median filtering, mean filtering, and Gaussian filtering. Image matching algorithms are mainly studied in two directions. One is based on classification matching, that is,
segmentation is performed first, then feature description is made, and then matching with the template; the other is based on the extraction of local feature points. In the template matching algorithm, it mainly focuses on the image gray matching algorithm. For example, a new representation method based on image gray value proposed by Dr. Li Qiang[1] of Tsinghua University, through segmentation, calculates the total gray value of each image and compares and sorts with adjacent blocks to realize the matching between image and template. In the fast recognition algorithm of geometric parts based on Fourier features proposed by Wei Zhenshan [2], a canny edge operator is selected to extract the image edge. In addition, there are recognition algorithms based on color features, such as image retrieval based on color spatial features proposed by Wang Tao[3], a part recognition algorithm based on surf feature proposed by Yuan Anfu [4], LBP descriptor based on a binary pattern proposed by T. Ojala [5] and moment invariant feature proposed by M. K. Hu [6]. With the increasing maturity of big data technology, the workpiece detection technology based on the neural network has become a research hotspot. For example, Huang Hongyan [7] and others proposed the shape recognition of mechanical parts based on a high-order neural network. The algorithm uses length, angle, center angle, and the angle between adjacent edges to represent the shape of parts, which makes it have rotation invariance. But this kind of method needs a large amount of data, and the cost of pre-processing is too high.

In the face of the above problems, this paper uses a two-level scale to extract Harris features respectively. On the one hand, the method is fast, on the other hand, the upper large-scale can better remove the noise, and then through the causal downward search for the corresponding feature points to obtain the accurate feature point location of the workpiece.

2. Related Work

The feature point detection algorithm can be traced back to Moravec's corner descriptor. In order to improve the reliability of the operator, Harris, and Stephens improved it, and once became the most widely used feature extraction operator. The speed of Harris algorithm is very fast. However, it has poor anti-noise performance and does not have scale invariance. Although the scale of the workpiece on the production line is relatively fixed, the background noise is relatively large. As shown in Fig.1, rust on the production line will produce a large number of feature points. Linderberg's Gaussian scale-space can suppress noise on a large scale, but the location of feature points will shift in a high-level scale, and the computational complexity is too high. In this paper, a two-layer scale is used to filter out the noise at the upper level and to find the exact location of the bottom layer from the causal downward projection of the scale space.

![Fig.1 A piece of iron with embroidery](image-url)
3. The causality of Gaussian scale-space

Linderberg assumed that Gaussian kernel is the only linear kernel satisfying the scale space theory. By convoluting the image with a series of Gaussian functions with different parameters, different scale space layer images are generated, and the Gaussian scale space of the image is constructed.

\[ G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{(x^2+y^2)}{2\sigma^2}} \]  

(1)

We can get the image \( L \) on a different scale by Gaussian convolution.

\[ L(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \]  

(2)

\( I(x, y) \) is the input image, \( \sigma \) is the spatial scale factor of the scale space, the size of \( \sigma \) determines the size of the smoothing range, and selecting the appropriate spatial scale factor is the key to build the scale space.

Fig. 2 is a Gaussian scale space generated by the continuous convolution of images. With the increase of scale, the image becomes more and more blurred, and the loss of details is more and more serious, but at the same time, it achieves a good denoising effect.

![Fig. 2 Flowers and the Gaussian scale-space](image)

Causality is the most important characteristic of scale space. It means that the characteristic points will not increase with the increase of scale, but the position will drift. By extracting features at two
different scales of the image, the number of feature points does not increase, but the location has changed or disappeared. Linderberg made a strict derivation of this in his paper.

![Image](corners_detected.png)

**Fig.3** The causality of Gaussian scale-space

4. Methods

Linderberg's theory tells us that we can obtain the feature points with strong anti-noise ability at the high level through the Gaussian scale space, and find the corresponding feature points by downward projection according to the causality, so as to obtain the accurate location information of the feature points. In order to speed up the speed, we take two measures: one is to construct only a two-layer scale, and the upper image size is reduced by half, and the scale parameter is selected as an empirical value of 1.3. The other way is to extract features in two-layer space by fast Harris algorithm.

The downward projection method is shown in Fig.4
In the image, the feature points detected in the upper image are projected downward, and the feature points are searched within the radius of 4 pixels. If more than one feature point exists in the range, the feature point with the closest eigenvalue is selected. The eigenvalue is the $H$ value of Harris operator, which is defined as follows.

$$M = \exp \left( \frac{x^2 + y^2}{2} \right) \begin{pmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{pmatrix}$$

$$I_x = \frac{\partial I}{\partial x}, \quad I_y = \frac{\partial I}{\partial y}$$

$$H = \text{DET}(M) - k \cdot \text{Tr}(M)$$

5. Results

Compared with the traditional Harris algorithm, our method has a strong anti-noise ability. Compared with the scale invariant operator sift, our method is simple and has a greater speed advantage.

5.1. scale invariant feature

Fig. 5 shows the effect of three methods in large-scale extraction for the structural object. It can be seen that the position of feature extraction has a certain offset. Fig. 6 is the feature extracted from the original image. Our method obtains the robust features and recovers the position of the feature points.

Fig. 5 extract of feature on the big scale
Experimental results show that our method is better than Harris operator and sift operator in scale invariance.

We use repeatability to measure the performance of the operator, which is the ratio of the number of repeated feature points to the number of all feature points in two images. That is,

\[
\text{Repeatability} = \left( \frac{R_{1,2}}{S_{1,2}} \right) \times 100\%
\]

\( R_{1,2} \) are the number of feature points matched in the two images. \( S_{1,2} \) are the number of all the feature points. Fig. 6 shows that our method is better than sift and Harris. In addition, due to the two-layer scale, the time complexity is slightly higher than Harris operator but much lower than the sift operator, as shown in Tab.1.

![Repeatability Graph]

**Fig.7** Repeatability
| scale | 1   | 1.5 | 2   | 2.5 | 3   | 3.5 |
|-------|-----|-----|-----|-----|-----|-----|
| SIFT(s) | 2.2633 | 2.7728 | 3.2354 | 3.6610 | 4.1200 | 4.5915 |
| Our method(s) | 0.3360 | 0.3281 | 0.3110 | 0.3100 | 0.3102 | 0.3089 |

**Tab.1** The time cost between Sift and our method

5.2. *The anti-noise ability*

The background noise of the workpiece is large due to factors such as oil stains and rust spots on the factory production line, which brings great interference to feature extraction. Harris is sensitive to noise, which is disadvantageous to subsequent processing. Due to the convolution of the original image at a large scale, the proposed method can effectively suppress the noise. Fig.7 shows the performance comparison of different algorithms in anti-noise.

![Harris on workspiece](image1)

(a) Harris on workspiece

![Sift on workspiece](image2)

(b) Sift on workspiece

![Our method on workspiece](image3)

(c) Our method on workspiece

**Fig.8** The anti-noise performance of the different method
6. Conclusions
Stable feature extraction is the key to workpiece detection in the production line. In this paper, we use the method of constructing a two-layer scale space to remove the noise interference and get the accurate position by downward projection. In addition, Harris corner points are extracted from each layer to improve the speed. The next step of our work is to calculate the size and shape of the workpiece based on the obtained feature information.

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