Image Matching Based on Improved SIFT Algorithm

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Abstract

To improve the resolution of different scales in different image matching accuracy and efficiency, this paper introduces an improved method based on scale invariant feature transform (SIFT) algorithm for image matching. The quasi Euclidean distance instead of Euclidean distance is as the similarity measure of feature descriptors to improve the SIFT feature matching efficiency. Experimental results show that under the condition of keeping the image matching rate and algorithm robust, the method can not only improve the matching accuracy but also shorten the matching time. The algorithm is possible and valid.

Keywords

SIFT algorithm, image matching, keypoints, quasi Euclidean.

1. Introduction

Image matching is one of the most active research areas in machine vision and serves as an important step in many applications. Image matching refers to using effective methods to analyze the consistencies or likelihoods in two or more images of the same object which are acquired in the different vision conditions, and find the most homologous image points among these images [1]. Nowadays, there are mainly two kinds of image matching methods: one is based on image gray scale matching and the other is based on image character matching. The first method is directly using image gray value to discover the best matching point, which algorithm is simple and high accuracy, it is mostly sensitive to illumination, scale, etc., but the amount of calculation is great too, so it is easy to fail in matching. The second method takes the image character as the matching measurement, such as image edge, image texture and image region statistical character. Compare with the first method, this kind of method has good anti-noise performance. it can be immune from illumination, scale and rotation.

SIFT (Scale Invariant Feature Transform) algorithm is proposed by David G. Lowe in 2004 after 5-year perfection and summary, and it is applied to extract local feature widely; the SIFT features are invariant to image rotations, illumination changes, scale changes and so on [2, 3].The SIFT features are local and based on the appearance of the object at particular interest points, which are invariant to image scale and rotation. They are also robust to changes in illumination, noise, occlusion and minor changes in viewpoint. But in some occasions SIFT cost much time, and it is very difficult to achieve real-time control. In this paper, we presented a improved image matching method based on SIFT by using quasi Euclidean and the experimental results demonstrate the usefulness of the method in image matching.

2. Introduction of SIFT Algorithm

The SIFT algorithm is widely used in image matching methods for that the SIFT feature is invariant to image rotations, illumination or scale changes [4]. The steps of the SIFT algorithm [5] are as follows:

2.1 Detecting the Local Extrema in Scale-space.

In order to detect the stabilized key-feature-points effectively, 2D Gaussian kernel [6] is defined as Equation (1):

$$G(x,y,\sigma)=\frac{1}{2\pi\sigma^2}e^{-(x^2+y^2)/2\sigma^2} \tag{1}$$

For a corresponding image I(i , j), the differential Gaussian scale-space (DOG scale-space) is proposed by using the different scales of the Gaussian kernel convolved with the image.

$$L(x,y,\sigma)=G(x,y,\sigma)\otimes I(x,y) \tag{2}$$

$$\begin{aligned}D(x,y,\sigma)&=(G(x,y,k\sigma)-G(x,y,\sigma))*I(x,y)\\&=L(x,y,k\sigma)-L(x,y,\sigma)\end{aligned} \tag{3}$$

Where I(x, y) is a function of the 2D original image, L (x , y ,σ) is a Gaussian image. (x, y) represents the pixels position , also named scale-space factor.

The SIFT key-feature-points are made up of the local extrema of D(x, y, σ); to detect the local maxima and minima points successfully, each point is compared with the pixels of all its 26 neighbors. If this value is the minimum or maximum, then this point is an extremum.

2.2 Locating the Extremum Accurately.

The SIFT algorithm determines the location and dimension of the extreme value point through the second-order Taylor expansion of the DOG function. Because the DOG operator is sensitive to edge responses and noise, we need use curve fitting to improve the stability of the keypoints, when the entire keypoint candidates have been found. The 3D quadratic function is fit to locate the keypoints in SIFT algorithm, it is shown in Equation (4):

$$D(\mathrm{X})=D+\frac{\partial D^T}{\partial \mathrm{X}}\mathrm{X}+\frac{1}{2}\mathrm{X}^T\frac{\partial^2 D}{\partial \mathrm{X}^2}\mathrm{X} \tag{4}$$

Take the derivative with respect to *X*, and set it to 0, we can get:

$$D(\hat{\mathrm{X}})=D+\frac{1}{2}\frac{\partial D^T}{\partial \mathrm{X}}\hat{\mathrm{X}} \tag{5}$$

If | *D(X)* | < 0.03, the extremum was rejected in experiments.

2.3 Keypoint Orientation Invariance.

To ensure that the descriptor possesses orientation invariance, we specify the direction parameters by using the gradient direction distribution characteristic of keypoint neighborhood pixels.

$$\begin{aligned}m(x,y)&=\sqrt{(L(x+1,y)-L(x-1,y))^2+(L(x,y+1)-L(x,y-1))^2}\\\theta(x,y)&=a\tan 2((L(x,y+1)-L(x,y-1))/(L(x+1,y)-L(x-1,y)))\end{aligned} \tag{6}$$

The gradient magnitude m(x, y) and orientation θ(x, y) of each image are pre-computed by using pixel differences. The SIFT feature points with location, scale and orientation are generated.

2.4 Generation of Feature Descriptor.

In order to achieve orientation invariance, the coordinates of the descriptor and the gradient orientations are rotated relative to the keypoint orientation. To creat the keypoint descriptor , firstly the gradient magnitude and orientation at each image sample point are computed in a region around the keypoint location. These samples are then accumulated in orientation histograms that summarize the contents over 4×4 subregions, the length of each arrow corresponds to the sum of the gradient magnitudes near that direction within the region. Finally, a 4×4×8 = 128 element feature vector is generated for each keypoint.

3. The Improved Image Matching Method

Because the feature vector is as high as 128 dimensional, the large amount of calculation will reduce the matching speed .When applied the SIFT algorithm matching image, we must calculate the distance between the feature points in an image to another image all the feature points, and each distance has 128 dimensional data, the complexity of the calculation was palpable.

Euclidean distance, the most common distance measurement standard, has been used as a matching rule in many image matching algorithms based on SIFT. In this paper, we present an improved SIFT image matching method based on quasi Euclidean distance[7,8]. with the quasi Euclidean distance replaced the Euclidean distance, and through the limit of geometric constraints to eliminate many mistakes on match point, the matching time is shortened, and the matching efficiency of algorithm is improved.

Euclidean distance refers to the linear distance between two pixels , in 2D space, it is defined as the following:

$$d = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \tag{7}$$

The quasi Euclidean distance is Euclidean matrix according to the level, vertical, and object collection segmented estimate all the Euclidean distance. It can be described as:

$$d_0 = |x_1 - x_2| + (\sqrt{2} - 1)|y_1 - y_2| \tag{8}$$

Obviously, calculation d_0 is simple than more than d, but the obtained values are small, we use appropriate linear combination αd instead of d_0, it can make the calculation simple and the calculation of deviation.

In a calculation of d, the SIFT algorithm need 128 times multiplication and a square root, the improved algorithm only need a multiplication. If the image is generated N keypoints of 128 dimensional, the reduction of multiplication computation is 127N respectively. Computing the distance of two points with the shortest eigenvector is the matched points of matching image .So in this way can obviously shorten the operation time and improve the efficiency of the algorithm.

Fig.1 Stereo images

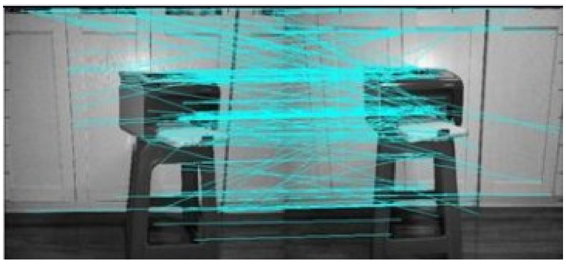

Fig.2. SIFT matching result

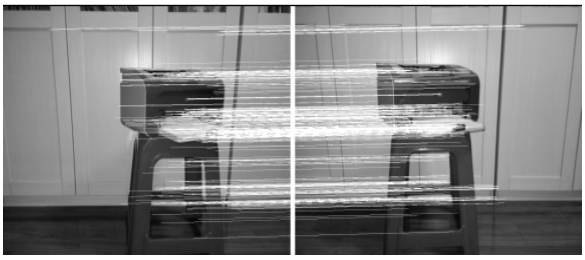

Fig.3. The result of improved algorithm

4. Experimental Results

The images used in the experiment are shown in Fig. 1, the reference image is taken from real environment. The matching result of SIFT algorithm and improved algorithm are shown in fig. 2 and fig. 3 separately. The improved algorithm can effectively increase the number of feature points, and matching result is accurate.

5. Conclusion

This paper describes a matching algorithm in image processing, Experimental results show that the improved SIFT matching algorithm based on quasi Euclidean distance is effective and feasible. This method can achieve real-time and accurate stereo matching, the complexity of calculation has been reduced, and the amount of calculation has been reduced greatly.

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