An improved sift image matching detection

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Abstract

Aiming at the problems - edge response in the traditional SIFT descriptor and the insufficient correct matching feature points, the work proposed a kind of improved SIFT Image Matching Detection Algorithm. The candidate key point was firstly detected by the SIFT algorithm; Canny edge detection algorithm was used to detect image edge points; it was judged whether the candidate key point needed to be eradicated by comparing whether the candidate key point equals to the coordinates of edge points; K-means clustering pattern, which is combined by the vector space cosine similarity and vector Euclidean distance similarity, was adopted to perform global image similarity matching. Finally, RANSAC algorithm was used to further get rid of the wrong matching. The experimental result indicates the improved method greatly enhances the stability of SIFT algorithmic and the accuracy rate of matching.

Keywords: SIFT operator, Canny operator, K-means cluster, accuracy rate, key point, edge detection

1 Introduction

Image matching technique has become the research focus in the fields of computer vision and digital image processing. At present, image matching methods are mainly based on two methods [1] of pixel and features. Especially the SIFT algorithm that is presented by David G. Lowe [2-3] in 1999, with favourable invariance property on the conditions of image rotation, measure scaling, affine transformation and change of view. Based on that the identification and matching of SIFT feature are used in many fields, such as target identification [4-5], image stitching [6], and mobile robot localization and mapping [7-8].

Even though SIFT algorithm is successfully applied in many fields, SIFT algorithm itself also has obvious defects, because the DOG operator adopted in SIFT algorithm has strong edge response; therefore lots of unstable edge response points exist in the produced feature points, and the Canny edge detection algorithm in this work removes unstable edge response points. In the field of engineering mathematics, the most common vector similarity measurement method is that the cosine similarity determines its degree of vector direction difference by comparing the included angle of the vector space between two vectors. The more consistent the direction is, the greater the similarity is; on the contrary, the similarity is less in the opposite direction. This similarity evaluation method only applies the direction information of the vector; therefore, this work proposes a kind of better similarity, the combination of included angle cosine similarity and the Euclidean distance. Finally, we use RANSAC to remove the wrong matching and mismatching. The experimental result indicates that this algorithm keeps the robustness of the previous algorithm, and meanwhile improves the accuracy rate of the algorithm stability and matching.

2 Feature extraction of the SIFT and Canny combination

Because the DOG operator used in SIFT algorithm will produce strong edge response, the generated feature points contain lots of unstable edge response points. Therefore, this work adopts Canny edge detection algorithm on the basis of the classic SIFT features to extract more stable features aiming at the edge response, providing a good foundation for the later feature matching. The feature extraction mainly includes following five steps.

1. Construct DOG scale space

In order to effectively detect the stable key point in scale space, Lowe [3] puts forward the DOG scale-space, which is produced by different scales of DOG and image convolution.

$$\begin{aligned} D(x,y,\sigma) &= \left[G(x,y,k\sigma)-G(x,y,\sigma)\right]*I(x,y) \\ &= L(x,y,k\sigma)-L(x,y,\sigma) \end{aligned}, \quad (1)$$

where k is the fixed parameter, $G(x,y,\sigma)=\frac{1}{2\pi\sigma^2}e^{\frac{-(x^2+y^2)}{2\sigma^2}}$, $I(x,y)$ is the original image, and σ is scale coordinate.

2. Detecting the extreme point of the scale space

In the process of detecting the scale space extreme value, the current detected pixel needs to compare with the 8 adjacent pixels at the same scale and the 9*2 pixel at the closely corresponding position of the 2 high and low scale.

3. Removing the unstable edge point

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For all of the candidate feature points detected by extreme value detection, it is needed to eradicate the unstable edge point by means of the 2 following steps.

The first step is to eradicate the unstable edge response point by means of 2*2 Hessian matrixes. The form of H matrix is

$$H = \begin{bmatrix} D_{xx} & D_{xy} \\ D_{xy} & D_{yy} \end{bmatrix}. \tag{2}$$

The stability measurement η is

$$\eta = \frac{\left(D_{xx} + D_{yy}\right)^2}{D_{xx}D_{yy} - D_{xy}^{\ 2}} < \frac{(\gamma+1)^2}{\gamma}, \tag{3}$$

where γ is the specific value between the maximum feature value and the minimum feature value, which is applied to control the stability of the feature point.

The second step is to eradicate the unstable edge point by means of Canny edge detection algorithm.

Firstly, we need to calculate the position of each feature point F_1 on the original image after eradicating unstable edge response by means of principal curvatures, and then use Canny algorithm to detect the edge point. For each edge point F_2, we use Canny to calculate the point set F_3 within the 3*3 field. Finally, we check if the coordinates are equal by performing comparison on the candidate key point F_1 and edge point F_2. The key point F_1 is abandoned if it's equal. If it's unequal, F_1 continues to compare with F_3. If something in point set F_3 is equal to the F_1 coordinate, the key point F_1 is abandoned. The key point F_1 is preserved if no equal points exist.

4. Calculating the direction of the key point

The DOG convolution image is used to determine the only direction of the feature point in order to make the feature vector satisfy the rotational invariance. The formula of calculating the gradient magnitude m and the direction θ is [11-12]:

$$m = \sqrt{\left(L_{x+1,y} - L_{x-1,y}\right)^2 + \left(L_{x,y+1} - L_{x,y-1}\right)^2}, \tag{4}$$

$$\theta = \arctan\frac{L_{x,y+1} - L_{x,y-1}}{L_{x+1,y} - L_{x-1,y}}. \tag{5}$$

In order to improve the stability of the gradient calculation, the neighbourhood gradient histogram with the feature point as the centre is calculated, and the peak value of the histogram represents the direction of the feature point.

5. Constructing the descriptor of the feature vector

After choosing 16*16 field with feature point as the centre, it is divided into 4*4 image subblocks, 8 directions of vector information of each pixel is identified, and thus the $4\times4\times8=128$ dimension feature vector can be generated. The illumination invariance of the vector can be improved by means of the uniformization on the feature vector.

3 Matching strategy improvement of feature vector

The classic SIFT feature matching is realized by calculating the Euclidean distance between all the feature points in an image and those in another image. For example, a feature point a_1 in the Image A wants to find an accurate matching point b_1 from the Image B, the Euclidean distance between the feature point a_1 and all the feature points in the Image B, and then b_1 is obtained after comparison. Because the Euclidean distance of all the features in the Image B should be calculated when matching is performed on each feature point, the calculated amount is large, and the information of feature points cannot be sufficiently used.

1. The following aspects are improved, and the feature points are separated into several kinds for performing K-means cluster on the stable SIFT feature points, the basic principle is that higher similarity exists between the same kind, but the difference is larger between different kinds.

2. The measurement form of the feature descriptor similarity is improved, and uses the combination of the Euclidean distance and included angle cosine to replace the Euclidean distance, thus sufficiently applies the size and direction of the feature vector, enhancing the accuracy rate.

3. Using RANSAC to cancel the wrong matching, and improve the accuracy rate.

3.1 FEATURE POINTS CLUSTER BY K-MEANS

The K-means plan is adopted in this work in order to perform matching on the feature points with similar descriptors during the matching. The process of calculation:

1. After inputting A and B images, the stable SIFT features are calculated, which are feature group des1 and des2, respectively.

2. Use K-means cluster feature to separate the feature group des l and des 2 into 5 groups, the 5 feature groups of the first group are des11, des12, des13, des14 and des15; and the 5 feature groups in the second group are des21, des22, des23, des24 and des25.

3. The cluster centre in the 5 feature groups of the first group are separately c11, c12, c13, c14 and c15, the cluster centre in the 5 feature groups of the second group are c21, c22, c23, c24 and c25, respectively. The closest cluster centre from the 5 cluster centres are found in the second group, and all the feature points with the c11 are used as the cluster centre to be matched with all the feature points of the closest cluster centre to the c11. Matching can be performed on the other feature groups in the first group accordingly.

3.2 USING THE EUCLIDEAN DISTANCE AND THE INCLUDED ANGLE COSINE AS THE SIMILARITY

In the classic SIFT algorithm, the Euclidean distance of SIFT feature vector is adopted to calculate the similarity between a pair of SIFT features in two images, thus only the size of the feature vector is used, but the direction of feature vectors are not sufficiently used, so this work uses both Euclidean distance and the included angle cosine. The distance between vectors satisfying the Euclidean distance and the direction between the vectors should satisfy the included angle cosine, thus the size and direction of the feature vector can be sufficiently used.

The Euclidean distance between two n dimension points $x=\left(x_1,x_2,x_3,...x_n\right)$ and $y=\left(y_1,y_2,y_3,...y_n\right)$ is identified as:

$$D_o\left(x,y\right)=\sqrt{\sum_{i=1}^{n}\left(x_i-y_i\right)^2}\ . \tag{6}$$

The included angle cosine is identified as:

$$\cos\theta=\frac{\sum_{i=1}^{n}x_iy_i}{\sqrt{\sum_{i=1}^{n}x_i^2}\sqrt{\sum_{i=1}^{n}y_i^2}}\ . \tag{7}$$

The data range for the included angle cosine is [-1,1]. The included angle of two vectors is smaller if the included angle cosine is larger. The maximum value 1 of the included angle cosine shall be performed when the direction of the two vectors is overlapped, when the direction of two vectors is completed opposite, the minimum value 1 of the included angle cosine shall be adopted.

3.3 USE RANSAC TO CANCEL THE WRONG MATCHING

This work adopts RANSAC to cancel the wrong matching. The input of the RANSAC algorithm contains a group of observed data and a parameter model appropriate for observing the data. The steps of RANSAC algorithm are as follows [13-15]:

1. There is a model, which is appropriate for the assumed inside point, which means all of the unknown parameters can be calculated from the assumed inside points.

2. The model zone obtained from 1. is used to test all of the other data, if some point is appropriate for the estimated model, which is recognized as the inside point.

3. If sufficient pints are classified into the assumed inside points, then the estimated model is sufficiently reasonable.

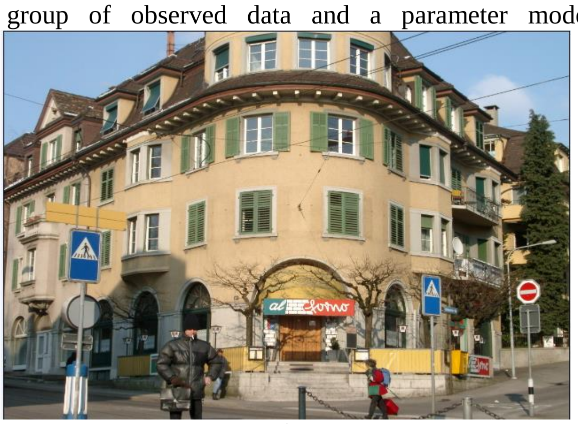
4. Use all the assumed inside points to reevaluate the model.

5. Finally, the model is evaluated by assessing the error rate of the inside points and the model.

4 Experimental result and analysis

The original SIFT feature matching algorithm and the improved algorithm are separately used to perform rectification on the image and analyse the result. The experiment is performed under the hardware environment of Intel(R) Core(TM)2 Duo CPU E6550 2.33GHz and 2 GB computer memory, and the simulated experimental environment is the MATLAB 7.8 of Windows XP.

(1) In the feature extraction phase, several experiments and data indicate, the feature extracted by the SIFT algorithm after being optimized by the Canny algorithm is more stable than the original SIFT feature, which meanwhile provides good basis for the later matching. 30 pairs of images are selected in the experiment; each pair is captured from different angles, the images of the same scene with different scaling, different rotation angles and view change are used as the required data of the experiment. Limited by the length of this work, one group of images will be mainly analysed in image 1; the size of the image is 640*480. The two images of this group are marked by the original reference image and the original image without rectification, respectively.



(a)Original reference image

(b)Original image without rectification

FIGURE 1 Original image

The unstable edge point is not favourably eradicated in the classic SIFT feature extraction, so the feature extracted by the algorithm in this work is more stable. The following image is the feature extraction result and the original one. Under the same conditions, the experimental result indicates that the SIFT feature presented in the first image is 1229, and the SIFT feature presented in the second image 2012. In the algorithm of this work, the feature extracted from the first image is 951, and the feature extracted from the second image 1551. 278 unstable edge points are removed in the first image feature, and 461 unstable edge points are eradicated in the second image feature. 23% edge points are averagely removed. These edge points are the wrong results which are generated when the image is affected by the noise, the feature point extracted by the algorithm of this work greatly enhances the robustness of the SIFT algorithm. The experimental results of 5 images are presented in the following Table 1.

(a)SIFT feature extraction (b)SIFT feature extraction

FIGURE 2 Original SIFT feature

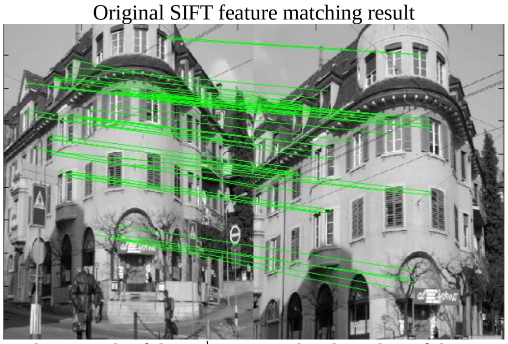
TABLE 1 Quantity comparison of feature points between the classic SIFT algorithm and the algorithm

	The 1st image	The 2nd image	The 3rd image	The 4th image	The 5th image
Feature points of classic SIFT	847	479	1535	936	596
Feature points extracted by the algorithm in this paper	604	299	1397	711	427
Unstable edge points eradicated by the Canny	243	180	132	225	169

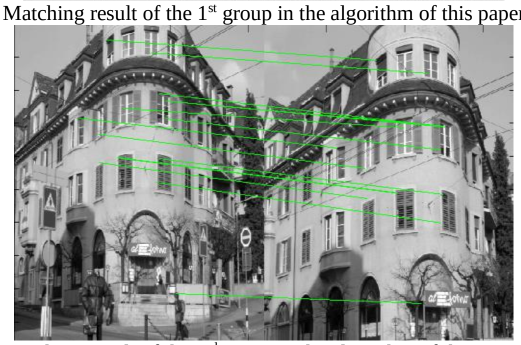
(2) In the phase of rectification, the original SIFT matching algorithm and the matching algorithm are separately used to perform feature matching on the Figure 1 in order to testify the validity of the algorithm. The final matching feature points of the original SIFT matching algorithm are totally 65. The feature matching in the matching algorithm of this work is used, the matching points of the first group is 70, the matching points of the second group 51, the matching points of the third group 29, the matching points of the fourth group 83, the matching points of the fifth group 50, and finally the matching points 283, which is 4 times of the previous algorithm. The experimental result is shown as the following figures.

Original SIFT feature matching result

Matching result of the 1st group in the algorithm of this paper



Matching result of the 2nd group in the algorithm of this paper



Matching result of the 3rd group in the algorithm of this paper

Matching result of the 4th group in the algorithm of this paper   Matching result of the 5th group in the algorithm of this paper

FIGURE 4 Feature matching

TABLE 2 Matching quantity comparison of feature points between the classic SIFT algorithm and the algorithm

	The 1st pair of image	**The 2nd pair of image**	**The 3rd pair of image**	**The 4th pair of image**
Matching feature points of the original SIFT matching algorithm	19	31	54	72
Matching feature points of the matching algorithm in this paper	49	102	224	280

The experimental results indicate that the matching feature points of the algorithm increase obviously compared to the original algorithm, which enhances the robustness of the feature and the stability of the matching.

5 Conclusions

On the basis of analysing the SIFT feature matching algorithm, this work puts forward that the improved accurate image matching algorithm based on the stable SIFT reduces the wrong matching rate, which improves the accuracy rate of the image matching. The work adopts Canny to remove unstable edge points on the classic SIFT feature, extracts the SIFT feature which has strong anti-noise capacity, and meanwhile performs K-means cluster on the extracted feature points, performs feature matching on the corresponding cluster area, Euclidean distance and the included angle cosine are adopted to be as similarity during matching, and completely apply the size and direction of the feature vector. Finally, the RANSAC algorithm is used to remove the mismatching. The algorithm in this work improves the stability and accuracy rate of the matching.

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References

[1] Stein A, Hebert M 2005 Incorporating Background Invariance Into Feature-based Object Recognition *IEEE Workshops on Application of Computer Vision,Breckenridge,CO,USA*

[2] Lowe D G 2009 Object Recognition from Local Scale-invariant Features *Proceeding of the Seventh IEEE International Conference on Computer Vision.Kerkyra,Greece* 1150-7

[3] Lowe D G 2004 Distinctive Image Features from Scale-invariant Keypoints *International Journal of Computer Vision* **60**(2) 91-110

[4] Zhang Shuzhen, Song Hailong, Xiang Xiaoyan, Zhao Yingnan 2010 Fast SIFT Algorithm Adopted to Realize the Target Identification *Computer System Application* **19**(6)

[5] Xiong Ying, Ma Huimin 2010 The Extraction and Application of the SIFT Feature for 3-D Objects *China Image Journal* **15**(5) 814-9

[6] Zhang Chaowei, Zhou Yan, Wu Sili 2008 Monitoring Image Automatic Combination Base on the SIFT Feature Matching *Computer Application* **28**(1) 191-4

[7] Stephen S, Lowe D G, Little J J 2005 Vision – based Global Localization and Mapping for Mobile Robots *IEEE Transactions on Robots* **21**(3) 364-75

[8] Ting T O, Rao M V C, Loo C K 2006 A novel approach for unit commitment problem via an effective hybrid particle swarm optimization *IEEE Trans, Power Syst.* **21**(1) 411-8

[9] Song Y, Chen Z, Yuan Z 2007 New chaotic PSO-based neural network predictive control for nonlinear process *IEEE Trans. Neural Netw.* **18**(2) 595-601

[10] Tao W B, Jin H, Liu L M 2008 Object segmentation using ant colony optimization algorithm and fuzzy entropy *Pattern Recognition Letters* **28**(7) 788-96

[11] Yin P Y, Chen L H 1997 A fast iterative scheme for multilevel thresholding methods *Signal Process* **60**(3) 305-13

[12] Cao L, Bao P, Shi Z K 2008 The strongest schema learning GA and its application to multilevel thresholding *Image and Vision Computing* **26**(5) 716-24

[13] Yin P P 2007 Multilevel minimum cross entropy threshold selection based on particle swarm optimization *Applied Mathematics and Computation* **184**(2) 503-13

[14] Zahara E, Fan S K S, Tsai D M 2005 Optimal multi-thresholding using a hybrid optimization approach *Pattern Recognition Letters* 2005 **26**(8) 1082-95

[15] Maitra M, Chatterjee A 2008 A hybrid cooperative-comprehensive learning based PSO algorithm for image segmentation using multilevel thresholding *Expert Systems with Applications* **34**(2) 1341-50

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