Sensors & Transducers, Vol. 170, Issue 5, May 2014, pp. 281-286

www.sensorsportal.com

Sensors & Transducers

Research on the Matching Algorithm Based on SURF

[1] Zhenjie HOU, [2] Dezheng YUAN, [1] Junsheng HUANG and [1] Zhuoran WU

1 School of Information Science and Engineering, Changzhou University, Changzhou, 213164, China
[2] School of Mathematics and Physics, Jiangsu University of Technology, Changzhou, 213000, China
E-mail: hhderek@163.com

Received: 27 February 2014 /Accepted: 30 April 2014 /Published: 31 May 2014

Abstract: Image matching is an important work in the field of computer image processing, the technology aligned same scene of two or more images obtained by different sensors in different or the same imaging conditions to determine the relationship between them. Based on the SURF algorithm, this paper adopts density threshold suppression strategies to reduce number of matched feature points; using the quasi Euclidean distance to complete the feature points matching process. Because the multiplication calculation only needs one time and decreases distance calculation deviation, the improved algorithm greatly reduced the feature points matching time and improves the matching accuracy. Through theoretical analysis and experimental contrast, demonstrates the reliability and validity of the algorithm. *Copyright © 2014 IFSA Publishing, S. L.*

Keywords: Image matching, Density threshold suppression, Quasi Euclidean, SURF.

1. Introduction

Image matching is an important work in the field of computer image processing especially in the navigation, the terrain matching and information prediction, environmental studies, pathologic studies, fingerprint identification and other fields. The technology aligned same scene of two or more images obtained by different sensors in different or the same imaging conditions to determine the relationship between them, such as translation or rotation [1].

Under the different imaging conditions, the imaging results will vary, even to the same object, the captured image also can have differences in different time, Angle etc. The research of image matching is to correct the differences through the space registration.

The matching algorithm based on image gray level matrix judge the results by matching similarity measure through such steps: first determine a real-time image window and do some search and matching calculation on the reference image. Therefore, similarity measure, window size, as well as the search strategy to these three factors will greatly affect the match result. When matching the image grayscale distortion is larger or geometric distortion, the matching algorithms tend to fail.

Stefano proposed a bounded part matching algorithm. The algorithm is obtained by Cauchy - Watts inequality, using new lower bound correlation function to effectively reduce the computation in the process of matching [2]. Based on sequential similarity algorithm, Takahito use a triangle inequality distance to get lower bounds on the child window of the registration window and the target window, and by setting threshold to determine whether to skip the search. The algorithm also reduces the amount of calculation of matching algorithm [3]. Luo Zhongxuan put forward a matching algorithm combining the wavelet variation and projection feature, in each layer setting wavelet threshold to reduce matching errors and improving matching performance [4]. Other related algorithm can be seen in [5], etc.

Based on characteristic matching algorithm is different from the matching algorithm based on gray level. Matching algorithm based on the characteristics firstly need to get the specific image characteristics, and then use the similarity measure as well as other related constraints to determine the geometric transformation acquired on the registration image [6]. Edge, the point of interest, and the classification of moment features are more common characteristics. For matching the image distortion, or noise disturbance, the image matching algorithm based on feature has certain robustness compared to the match algorithm based on gray level. But due to the differences in the extraction of image characteristics computation, image feature matching performance also has bigger difference, and the accuracy is not high.

2. SURF Feature Points Matching Algorithm

SURF called the Speed - Up Robust Features, is a kind of scale invariant image feature point extraction and feature points description algorithm. It is an improved SIFT (Scale Invariant Feature Transform) algorithm proposed by Bay [7]. The performance of SURF algorithm in illumination, perspective changes invariant is close to SIFT algorithm, its speed has improved greatly than SIFT algorithm [8].

Integral image is an original image after integration image, it computes a rectangular region pixels and integral image calculation chart is as follows (Fig. 1):

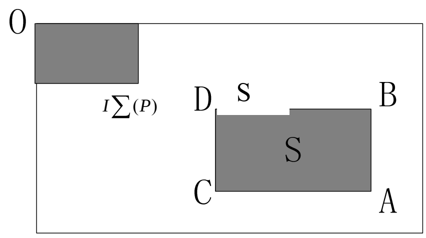

Fig. 1. Integral image calculation diagram.

As shown in Fig. 1, set P (x, y) is a point on the integral image, the point value of images is an integral value on the rectangular area from the origin to the point. Integral formula is as follows:

$$I\sum(P) = \sum_{i=0}^{i<x}\sum_{j=0}^{j<y} I(i, j), \quad (1)$$

The I (I, j) is the pixel value at the point (I, j), $I\Sigma(P)$ is P (x, y) value on integral image.

After integral calculation, only need the addition and subtraction operations to get the pixels sum of any piece of rectangular area in the original image and does not need to calculate the integration. Compared with ordinary integral operation, the greater the rectangular area, the more computation time can be saved using the integral image arithmetic. As it is shown in Fig. 1 the S area of the pixel can use 2 subtractions and 1 addition to represent:

$$S = A - B - C + D, \quad (2)$$

SURF use approximate Hessian matrix to test point of interest, and use points chart to improve the efficiency of interest point detection [9, 10].

SURF algorithm can accelerate the extracting speed of interested point by using integral image because of taking another important approximation: use box type filter to approximate Gaussian kernel function. Box type filter is also known as frame filter. The filtering results of the original image using box-type filter can be computed by using the integral image, and the integral image can greatly reduce the integral operation time, and then improve the algorithm performance.

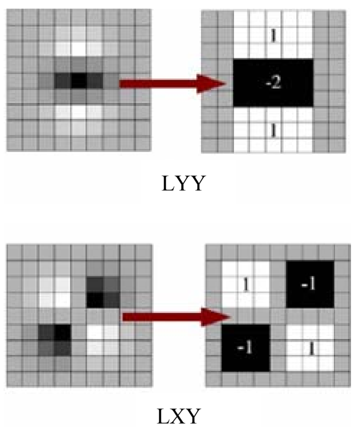

Fig. 2. Box filter.

The scale invariance of image matching requires image layering to establish the scale space of the image, and then search feature points in different scale space. Using image pyramid usually to achieve scale space. The first step to build image pyramid is to use different scale factor of Gaussian function to convolution with original image, and then to send a down sample processing, can obtain much higher levels of image pyramid. Interested points of SIFT algorithm are determined by the local extremum positioning in DoG space. DoG response image can be obtained by adjacent layer subtracting in the image pyramid, and all response images constituted DOG space. For SURF, the time spent that the original images are processed using different size of the filter is the same through the application of the integral image. Size of 9×9 approximate template is corresponding to the initial scale template, can be used to approximate 2 order partial derivative filter of σ=1.2. If using S to represent the approximation template scale, S=σ=1.2 at this time. The scale space of SURF is built by the approximate template convolution with the original image, and then gradually increases the template for the other layers of scale space. Due to the requirements of approximate template must have odd number and existing center pixel, all the difference between a template numbers is even.

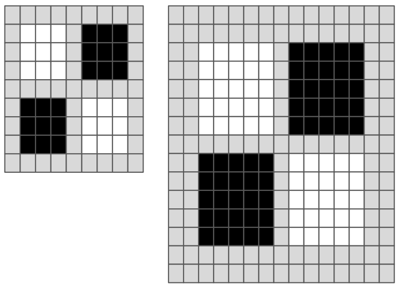

Fig. 3. 9×9 and 15×15 template.

Approximate template is ordered by pixel difference that next to another template. As shown in table 4, every 4 templates is order 1. The first order difference between the template is 6 pixels, and then to 12, 24, 48. At the same time, the initial value of the current order is the second layer value of the pre-order template. Because the degradation speed of the number of the interested points is very fast in scale direction, usually select 4 as the order.

When the image resolution is big, the order number and filter step should also make a corresponding adjustment.

Table 1. Parameters of template (order=4).

Order	Tem 1	Tem 2	Tem 3	Tem 4
1	9	15	21	27
2	15	27	39	51
3	27	51	75	99
4	51	99	147	195

3. Improved SURF Algorithm

Compared to SIFT, due to the use of the integral image strategy, the computing performance of SURF algorithm is greatly improved, but the description of the feature point still occupy a larger operation time. At the same time there is also a matching feature points on the phenomenon of mismatch. So in this paper, an improved SURF algorithm is used based on the strategy of density threshold suppression feature point extraction algorithm to reduce the number of feature points extraction, simultaneously using standard Euclidean distance instead of Euclidean distance to improve matching speed, at the same time considering the difference of the feature points scale to improve the correctness of the matching algorithm [11, 12].

3.1. Extracting Feature Points Based on the Strategy of Density Threshold Suppression

Shown in the Fig. 2, a number of feature points is very large, and its distribution is uneven. And under the condition of matching area is only a small area between two images, the algorithm will waste a lot of computation time for the description of the feature point. So this paper uses density threshold suppression strategy to reduce the feature point extraction.

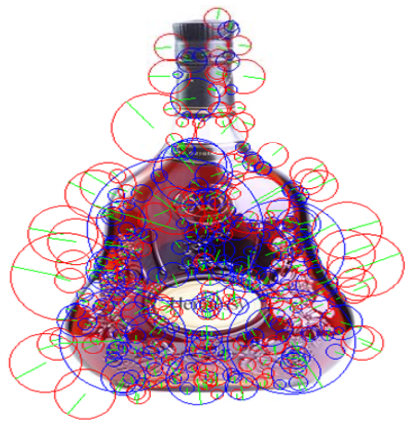

Fig. 4. Feature points extraction (0.0001 f) spot response threshold.

Specific image feature point extraction steps as follows:

1) The features of point positioning.

After scale space is created, the scale of the point (x, y) in the scale space image is σ, its corresponding Hessian matrix is defined as follows:

$$H(x,\sigma) = \begin{bmatrix} L_{xx}(x,\sigma) & L_{xy}(x,\sigma) \\ L_{xy}(x,\sigma) & L_{yy}(x,\sigma) \end{bmatrix}, \quad (3)$$

Hessian determinant of a matrix can be approximately expressed as:

$$\det(Hessian) = D_{xx}D_{yy} - (\omega D_{xy})^2, \quad (4)$$

The ω is a weight coefficient of a fixed value. Studies have shown that taking ω= 0.9 didn't affect the result of the experiment. When the determinant of a matrix is greater than the specified threshold, will be the next step. Selected points as characteristic points of requirement are in the current layer, the pre-layer and the next layer of each 3*3 neighborhood of the point adopt maximum suppression, and larger than other 26 response values. Finally interpolate the scale space to determine the location of the feature points.

2) The feature point selection.

In the previous step, feature points set was determined, we will filter collection for the feature points. First of all, the whole image is divided into several small square areas, and set a threshold value. If the area of feature points reach specified threshold, remove all other feature points in that area. Small square area feature point density is ρ, calculating formula is

$$\rho = \mathrm{N} / \mathrm{S}, \tag{5}$$

where N is the existing feature points in square area, S is the square area pixel points. Extracting feature points based on the strategy of density threshold suppression can effectively reduce the number of feature points, at the same time make the distribution of feature points is relatively uniform. Due to participate in feature points described to reduce the number of feature points, the improved algorithm can effectively reduce the computation of SURF.

3.2. Feature Point Description

1) The main direction.

Set s is the scale of the current feature point, then the main direction of calculation method is as follows: first, in 6s circular neighborhood calculate Haar wavelet of all feature points in the x, y direction. Wavelet sampling step size is s. Second, do a Gaussian weighting processing. Interests points as the center demanded by the weighted operation, using Gaussian function (σ=2s) to weight all of the response. Third, to angle for π/3 fan, around the point of interest for a cycle, every 5 degree calculation again. Each calculation required adding response in the fan area. For established circular neighborhood, traverse a circle can get 72 new vectors. Fourth, in the previous step of obtaining 72 vectors, select the longest vector as the main direction of the feature points.

2) Vector description.

The description of the vector is in the square neighborhood 16 sub-regions are divided to take independent operation. Similar with the description of the main direction methods, child vector description of SURF also need to calculate Haar wavelet of all feature points in the x, y direction of the response. So for each of the feature points in each area, can be calculated to get its response dx, dy. In all child area after the response calculation of feature points, the same to the feature point as the center for Gaussian weighted (σ=3.3). At the same time in order to describe the Haar wavelet in the x, y direction, need to add the absolute value of dx, dy. So, for positive direction of neighborhood each area has 4 quantities, and. Each child area obtained four dimensional feature vector:

$$v = (\sum \mathrm{d}_x, \sum \mathrm{d}_y, \sum |\mathrm{d}_x|, \sum |\mathrm{d}_x|), \tag{6}$$

3) Finally, merging vectors of 16 sub-areas will receive a 64-dimensional feature vector. For the 64-dimensional feature vector normalization processing is required, the characteristics of child description method has characteristics of luminance and scale invariance.

3.3. Feature Points Matching Based on Quasi Euclidean Distance

Two-dimensional plane of the Euclidean distance between two points is as follows:

$$D = \sqrt{(x - x_0)^2 + (y - y_0)^2}, \tag{7}$$

Quasi Euclidean distance is to use quasi European-style matrix in the form of a block of Euclidean distance estimation:

$$D_0 = |x - x_0| + (\sqrt{2} - 1)|y - y_0|, \tag{8}$$

Using SURF, each feature point vector description is 64 D and 128 D, calculating Euclidean distance between two feature points need 64 computing multiplication and square root operations at a time.

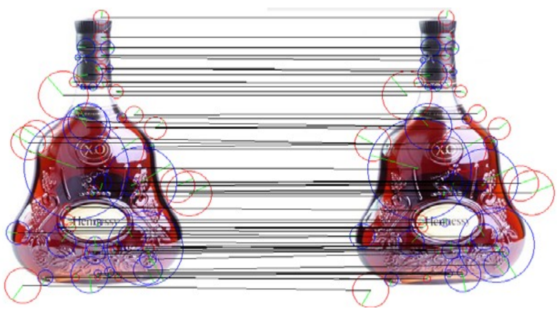

Fig. 5. Feature points matching.

So we use the quasi Euclidean distance to replace the Euclidean distance, the calculation only needs one time of multiplication, greatly reduce the time of feature points matching. At the same time using the quasi Euclidean distance the distance is smaller than Euclidean distance, so can decreases the distance calculation deviation and improve the matching accuracy.

4. Experiments and Results Analysis

4.1. Extracting Feature Points Based on Density Threshold Suppression Experiments

The experiments based on the density threshold suppression of feature points extraction shown in Fig. 6.

In Fig. 6, the parameter N is the number of feature points in the small square area, the parameter S is the pixel points number in small area. Feature points as shown in Table 2.

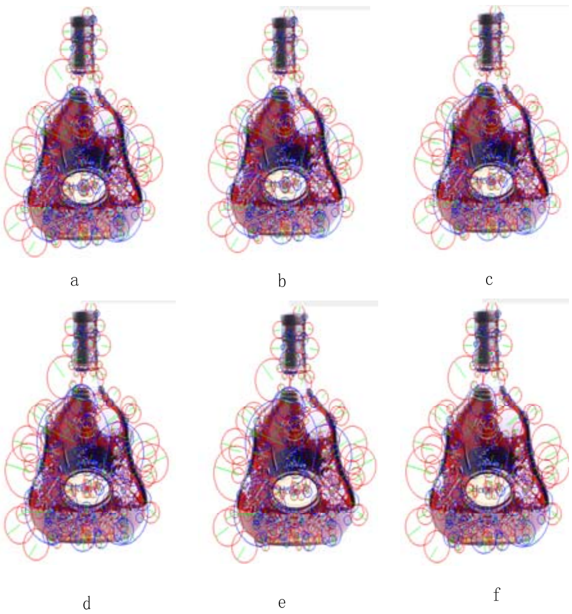

Fig. 6. Extracting feature points based on density threshold strategy (spot reaction threshold value: 0.0001f, N: 1) normal extracting; b. S=4; c. S=9; d. S=25; e. S=64; f. S=100).

Table 2. Extracting feature points based on density threshold strategy (N = 1).

S	Number of feature points	Time (ms)
Normal	359	450
4	349	442
9	337	429
25	315	409
64	277	374
100	258	350

Experiments show that based on the strategy of density threshold suppression feature point extraction algorithm can effectively reduce the number of feature points and the description time of the feature points. The algorithm effectively improves the operation efficiency.

4.2. Experiments Based on Quasi Euclidean Distance

Experiments based on quasi Euclidean distance shown in Fig. 7.

From the Table 3 we can see that the improved algorithm reduces the error matching points and calculating time, but at the same time reduces the total number of matches.

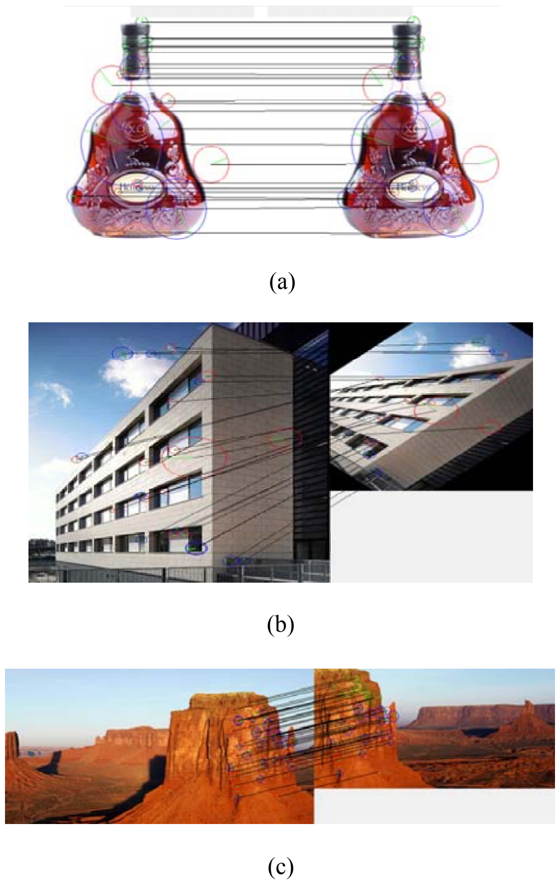

Fig. 7. Experiments based on the quasi Euclidean distance(quasi minimum Euclidean distance/quasi minimum Euclidean distance = 0.64).

Table 3. Experiments based on the quasi Euclidean distance.

Matching image	Original algorithm (error match number)	Improved algorithm (error match number)	Original matching time (ms)	Improved matching time (ms)
Bottle	70 (9)	25 (1)	110	90
Building	66 (10)	25 (1)	105	85
Desert	59 (2)	50 (0)	167	133

5. Conclusions

Image matching is an important work in the field of computer image processing. Based on the SURF algorithm, adopts density threshold suppression strategies to reduce number of matched feature points; using the quasi Euclidean distance to complete the feature points matching process. Because the multiplication calculation only needs one time and decreases distance calculation deviation, the improved algorithm greatly reduced the feature points matching time and improves the matching accuracy. Through theoretical analysis and experimental contrast, demonstrates the reliability and validity of the algorithm.

Acknowledgements

This work is supported partly by the National Natural Science Foundation of China under Grant No. 61063021.

References

[1]. Lei Zhao, Zhenjie Hou, An improved image registration method of SIFT, *Computer Engineering*, Vol. 12, 2010, pp. 226-228.

[2]. Luigi Di Stefano, Stefano Mattocia, Federico Tombari, ZNCC-based template matching using bounded partial correlation, *Pattern Recognition. Lett*, Vol. 26, Issue 14, 2005, pp. 2129-2134.

[3]. Takahito Kawanishi, Takayuki Kurozumi, Kunio Kashino, etc., A fast template matching algorithm with adaptive skipping using inner-subtemplates' Distances, *in Proceedings of the ICPR*, Vol. 3, 2004, pp. 654-657.

[4]. Luo Zhongxuan, Liu Chengming, Fast algorithm of image matching. *Journal of Computer Aided Design & Computer Graphics.* Vol. 17, 2005, pp. 966-970.

[5]. Zhenjie Hou, Research on 3D object rounding photography systems and technology, *Lecture Notes of Computer Science (LNCS),* 7473, 2012, pp. 152-158.

[6]. Zhenjie Hou, Research on genetic segmentation and recognition algorithms, *Lecture Notes of Computer Science (LNCS),* 7473, 2012, pp. 454-460.

[7]. Herbert Bay, Andreas Ess, Tinne Tuytelaars, etc. Speeded-up Robust Features (SURF), *Computer Vision and Image Understanding*, Vol. 110, Issue 3, 2008, pp. 346-359.

[8]. Herbert Bay, Tinne Tuytelaars, Luc Van Gool, SURF: Speeded-up Robust Features, in *Proceedings of the* 9th *European Conference on Computer Vision,* 2006, pp. 404-417.

[9]. C. Ford and D. Etter, Wavelet basis reconstruction of no uniformly sampled data, *IEEE Trans. Circuits and Systems II*, Vol. 45, Issue 8, 1998, pp. 1165–1168.

[10]. Zhenjie Hou, Study on traditional camera calibration, *Journal of Information*, Vol. 15, Issue 11(A), 2012, pp. 4393-4398.

[11]. W. K. Carey, D. B. Chuang, S. S. Hemami, Regularity-preserving image interpolation, *IEEE Transactions on Image Processing*, Vol. 8, 1999, pp. 1293-1297.

[12]. G. Casciola, L. B. Montefusco, S. Morigi, Edge-driven image interpolation using Adaptive Anisotropic Radial Basis Functions, *Journal of Mathematical Imaging and Vision*, Vol. 36, 2010, pp. 125–139.