2013 Ninth International Conference on Intelligent Information Hiding and Multimedia Signal Processing

An Improved SIFT Algorithm Based on FAST Corner Detection

Wu Lifang
College of Electronic Information and Controll Engineering.
Beijing University of Technology.
Beijing, China.
lfwu@bjut.edu.cn

Gao Yuan
College of Electronic Information and Controll Engineering.
Beijing University of Technology.
Beijing, China.
u09021130@emails.bjut.edu.cn

Zhang Jingwen
College of Electronic Information and Controll Engineering.
Beijing University of Technology.
Beijing, China.
zhangjingwen@emails.bjut.edu.cn

***Abstract*—In this paper, we propose an improved SIFT algorithm based on FAST corner detection. We first estimate the level of the pyramid by the size of the image. Then, at each level, we estimate the threshold by the image content. By the threshold, we implement the FAST corner detection. At each level, the FAST corner detection, generation of SIFT descriptors and coordinate mapping are implemented by Wagner's idea. The experimental results show that our proposed algorithm has the similar matching performance and runs faster.**

Keywords-SIFT descriptor; FAST corner detection; Image matching

I. INTRODUCTION

Image matching is a hot research spot in the Virtual reality and Computer vision fields. Many researchers made a large number of works on it. but the former proposed matching algorithms were sensitive to the variation of scale, rotation, illumination, affine transform. In 2004, David Lowe proposed a new features detection algorithm, SIFT(Scale Invariant Feature Transform)[1], the SIFT descriptors are robust to the variation of scenario part shade, rotation, zoom, Point of view. SIFT has been utilized in target recognition, image restoration and image stitching since it was proposed.

However, there are still some problems in the use of SIFT. It is difficulty to find an optimal threshold. There are usually about 2000-4000 SIFT points in an image and the dimension of the SIFT descriptors is too high, so that there are usually lots of data in an image. Due to these problems, some improved algorithms were proposed. Zhao et al used two concentric circles with 12 bins each to replace the 4x4 subregions, and then calculated the gradient orientation and magnitude of the pixel in the two concentric circles, they referred to the original SIFT algorithm to work out a 24 dimensional vector with the gradient histogram[2]. Yu et al proposed a way to reducing the descriptor dimensions through the image Radon transform[3] in 2011. Yan Ke at al used PCA to reduce the SIFT feature descriptor dimensions[4], and have been achieved good results. Mortensen, Eric N. et al created a descriptor combined with the global information[5] , reducing the matching error rate which was caused by similar local information, but the amount of calculation was large, and it did not the characteristic of the scale invariant because the range of the global vector size was fixed. Moreno et al used the Gabor filter to improve the SIFT descriptor[6], made it more suitable for high accuracy requirement scene, but the calculation was more complex. And there have been a report describe how to improve the scale space, Zhang Yu created a DoM(Difference of Means) pyramid to replace the DoG (Difference of Gaussian) pyramid[7], it is generated by integral images, because using the integral image could quickly and easily process images with a mean filter. This algorithm reduced much time cost to detect the features, but their calculation of descriptor become complex. Daniel Wagner et al proposed a way to improve SIFT algorithm based on FAST corner detection[8],[9] to achieve pose tracking on mobile phone[10].

But Daniel's algorithm could not provide optimal fast corner detection to different image or different sales of the same image because of the constant threshold, and the constant level of image pyramid made the large image don't have enough scales and the small image have calculation of redundancy. To solve these problem, we propose an improved SIFT algorithm further. We calculate the image threshold by a gray level difference measure before run the fast corner detector to improve the efficiency of features extraction, and the level number of the image pyramid is determined by the image size, it makes the algorithm adaptive to images of different scales.

The remaining part of the paper is as follows: in next section, we describe the proposed algorithm in details. We proposed a new idea of generating image pyramid and estimating the threshold by the size of image. in third section we show some experimental results. Finally, we conclude the paper in Section 4.

II. THE IMPROVED SIFT ALGORITHM

In this paper, we first estimate the level of the pyramid by the size of the image. Then, at each level, we estimate the threshold by the image content. By the threshold, we implement the FAST corner detection. At each level, the FAST corner detection, generation of SIFT descriptors and coordinate mapping are implemented by Wagner's idea. We use the FAST corner detector instead of generating DoG pyramid to detect the SIFT points, therefore, the algorithm is speed up. The framework of our algorithm is shown in Figure 1.

978-0-7695-5120-3/13 $26.00 © 2013 IEEE
DOI 10.1109/IIH-MSP.2013.59

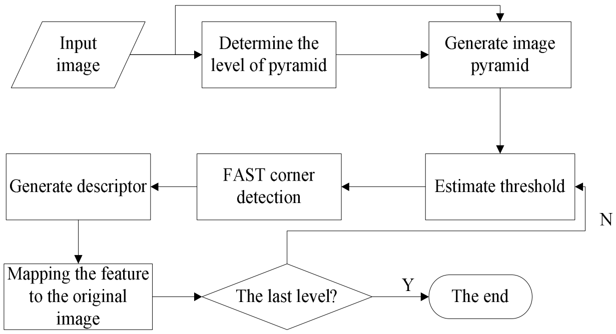


Figure 1. Framework of the proposed algorithm

Fast corner detection is implemented by Edward Rosten's algorithm[9], The SIFT descriptors generation is implemented referring to Lowe's idea[1].

A. Estimation of image pyramid

We use FAST corner detection to obtain the feature which do not need scale information. However, in order to ensure that our approach is scale invariant, it is necessary to detect the feature points in the images of different scale. for an input image, how many scaling levels is enough? We estimate it by the image size. We estimate the level number by Equation(1).

$$levels = \log_{\sqrt{2}}(\min(w1, h1)) - \log_{\sqrt{2}}(\min(w2, h2)) \quad (1)$$

Where, w1 and h1 are the width and the height of the original image. w2 and h2 are the width and the height of the top image, which are generally assigned as 4.

B. FAST corner detection and the threshold estimation

FAST corner detection is proposed by Edward Rosten and Tom Drummond in 2006. In order to determine if a pixel p is a corner. We first draw a circle centered as the pixel *p* as shown in Figure 2. Then we compute the absolute difference between each pixel on the circle and the pixel p. and then we count the number of differences bigger than the threshold as shown in Equation (2). If N is bigger than 75% number of the pixels on the circle, the pixel p is thought as a corner.

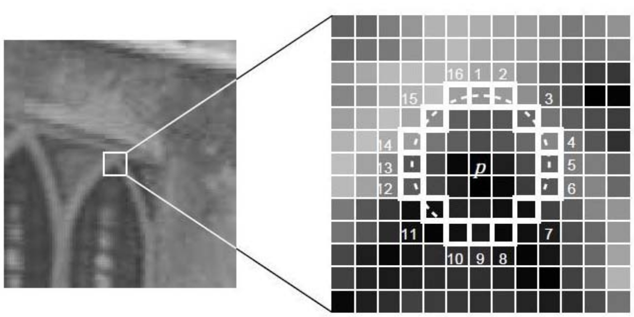


Figure 2 illustration of FAST corner detection

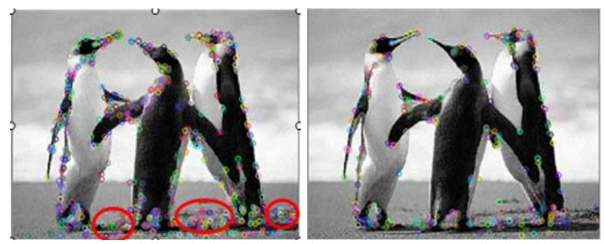
$$N = \sum_{x\forall(circle(p))} |I(x) - I(p)| > \varepsilon_d \quad (2)$$

Where, I(x) is a gray level of any point in the circle, I(p) is the gray level of the point p, ε_d is the threshold. In Wagner's paper[10], ε_d is a constant, but in our paper it is determined by the averaging variance of the gray level automatically.

$$\varepsilon_d = \sum (g(i) - \bar{g}) / n \quad (3)$$

Where, g(i) is the gray level of the i^{th} pixel in the image, $\bar{g}$ is the average of the image. And n is the number of pixel in an image.

Figure 2 show an image and the detected SIFT points using Wagner's algorithm and our improved algorithm respectively. From Figure 2 we can see that the traditional algorithm get a lot of redundant points, which are marked in the ellipse.


(a) from traditional algorithm (b) from our proposed algorithm
Figure 3. comparison of SIFT points from different algorithm

III. EXPERIMENT RESULT

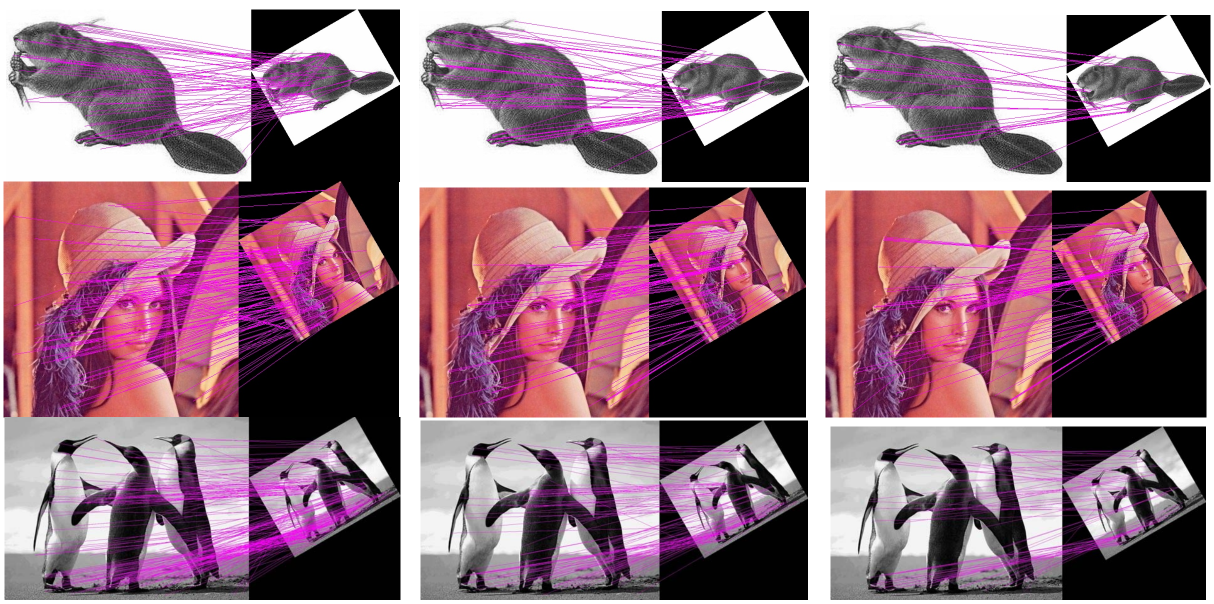
We compare our proposed algorithm with the Lowe's and Wagner's algorithm. We test the robustness of our proposed to image rotation and scale and speed. All the approaches are run on a PC with CPU 3.3GHZ, Single core i5, RAM 4GB.

We test how scaling and rotation influence the matching. The experimental results are shown in Table 1 and Table 2 respectively.

From Table 1 and Table 2 we can see that the averaging running time of our approach is about 1/4 of the original SIFT[1], and it is about of Wagner's improver algorithm[10]. In comparison, the original algorithm is robust to the image rotation, while our approach is robust to only the rotation of 90 and 180 degree. Three approaches are all robust to both scaling and rotation. Some example results are shown in Figure 4.

TABLE 1 Influence of image rotation to matching results

Rotation		**30°**	**60°**	**90°**	**120°**	**150°**	**180°**
Lowe's	The average number of matching points	350	385	379	322	377	705
	Average running time (second)	5.028	5.409	9.927	4.68	5.029	9.995
Wagner's	The average number of matching points	196	203	1003	181	211	925
	Average running time (second)	3.468	3.427	2.943	3.578	3.473	3.154
Ours	The average number of matching points	100	100	551	96	103	512
	Average running time (second)	1.341	1.311	1.451	1.414	1.347	1.463



(a) Lowe's approach (b) Wagner's approach (c) Ours

Figure 4 Influence of scaling and rotation to the matching results

TABLE 2 Influence of image scaling and rotation to matching results

Scaleing to the original size (rotation angle)		**2.0(0)**	**1/2(0)**	**2.0(30°)**	**2.0(90°)**	**1/2(30°)**	**1/2(90°)**
Lowe's	The average number of matching points	158	70	135	171	38	59
	Average running time (second)	9.131	4.29	12.345	11.334	1.820	1.560
Wagner's	The average number of matching points	177	145	83	185	43	105

	Average running time (second)	6.259	1.596	7.910	6.578	2.002	1.602
Ours	The average number of matching points	102	91	58	129	27	58
	Average running time (second)	2.016	0.635	2.475	1.809	0.873	0.701

IV. CONCLUSION

In this paper, we propose an improved SIFT algorithm. The experimental results show that our proposed algorithm runs faster, and the matching performance is almost similar to that of the original algorithm. Therefore, our approach could be utilized in some application scenario of requiring fast matching and lower matching accuracy.

V. REFERENCES

[1] David G. Lowe, “Distinctive Image Features from Scale-Invariant Keypoints”, Int. Journal of Computer Vision, Vol.60,No.2, pp.91-110, 2004.

[2] Zhao, Lei, and Zhen-Jie Hou. "Improved Image Registration Method of SIFT [J]." Computer Engineering 12 (2010): 080.

[3] Yu, Li-Li, and Qing Dai. "Improved SIFT Feature Matching Algorithm." Computer Engineering 2 (2011): 074.

[4] Yan Ke, and Sukthankar Rahul. "PCA-SIFT: A more distinctive representation for local image descriptors." Computer Vision and Pattern Recognition, 2004. CVPR 2004. Proceedings of the 2004 IEEE Computer Society Conference on. Vol. 2. IEEE, 2004.

[5] Mortensen, Eric N., Hongli Deng, and Linda Shapiro. "A SIFT descriptor with global context." Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on. Vol. 1. IEEE, 2005.

[6] Moreno, Plinio, Alexandre Bernardino, and José Santos-Victor. "Improving the SIFT descriptor with smooth derivative filters." Pattern Recognition Letters 30.1 (2009): 18-26.

[7] Zhang Yu, Zhu Dan, and Wang Yuliang,”Improved Fast Feature Matching Method Of SIFT ”, Microcomputer Information, Vol.34,No.2, pp.220-222, 2008.

[8] Trajković, Miroslav, and Mark Hedley. "Fast corner detection." Image and Vision Computing 16.2 (1998): 75-87.

[9] Rosten, Edward, and Tom Drummond. "Machine learning for high-speed corner detection." Computer Vision–ECCV 2006. Springer Berlin Heidelberg, 2006. 430-443.

[10] Wagner, Daniel, et al. "Pose tracking from natural features on mobile phones." Proceedings of the 7th IEEE/ACM International Symposium on Mixed and Augmented Reality. IEEE Computer Society, 2008.

[11] Kumar, G. Kishore, GV Raghavendra Prasad, and G. Mamatha. "Automatic object searching system based on real time SIFT algorithm." Communication Control and Computing Technologies (ICCCCT), 2010 IEEE International Conference on. IEEE, 2010.