Some Experiments on Corner Tracking for Robotic Tasks

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Abstract. In this paper, we present a comparison of the performance of Harris and SUSAN corner detection applied to corner tracking tasks in robotic vision. We have tested some corner refining algorithms on both methods and measured their performance when we applied to real images of a real-time sequence. We conclude that for the Harris method, a correlation step using an ideal corner model can improve stability in corner detection. In the other hand, it is better to use SUSAN algorithm without using the correlation step because it degrades its performance. We show also successful applications running at about 8 Hz for both corner detection methods.

1 Introduction

Current approaches for visual feature tracking include corners, blobs and edges [1]. Nevertheless, there are some unsolved problems in tracking systems; for example, complex scenes, occlusion problems, moving objects, highlights and reflections, significant illumination changes and motion blur.

Interest points or salient points are points that possess unique properties in an image. Salient features can describe unique objects in an image. One of the most often used features to describe salient point is cornerness property. A corner is a point with a high curvature in the intensity space that can be detected from the discontinuities on the neighborhood of a pixel.

Corner tracking has been used for many applications as diverse as robot visual localization [1], robot homing tasks using omni-directional vision [2], human-computer interfaces for augmented reality [3][4], scene modelling [5] or traffic detection [6].

However, its use in outdoor environment has not been intensively tested. Work to find optimal parameters and performance evaluation of corner tracking algorithms remain to be done. Our problem is to determine which algorithm implement in a robotic corner tracking system for indoor and outdoor environments. Our main application is directed toward characterizing landmarks robustly along an image sequence acquired by a mobile robot during the execution of a navigation task.

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We have compared the Harris and SUSAN corner detection algorithms implemented with some minor refinements. We present the details of our experiments later in this paper. We have proposed two tests to measure performance of corner detection algorithms: i)evaluation of corner detection algorithms on benchmark images and, ii) a stability test. First test is used to find optimal tuning parameters for the two corner detection algorithms compared in this paper. The second test proves stability of corner detection when illumination changes are significant. We also present two sequences where Harris and SUSAN algorithms perform well in complex environments.

2 Problem formulation

2.1 Harris corner detection

Harris corner detection algorithm was originally developed for robotic applications[7]. Its goal was to match corner points in stereo image pairs to enable a 3D reconstruction of the environment. Its work was an improvement of the work by Moravec [8], who has noted that the difference in intensities of adjacent pixels in edges and uniform regions of an image are small, but at corners the same difference is significantly high in all directions.

Computation of the cornerness property in this method is carried out by convolving a Gaussian mask with the Hessian matrix H of the intensity function of the image and analyzing the resulting matrix M.

$$M = e^{-\frac{u^2+v^2}{2\sigma^2}} \otimes H = \begin{bmatrix} \alpha & 0 \\ 0 & \beta \end{bmatrix} \tag{1}$$

with $\otimes$ a convolution operator.

Cornerness *R(x,y)* of a point (x, y) is then computed as follows:

$$R(x, y) = det(M) - k \cdot (trace(M))^2 = \alpha\beta - k(\alpha + \beta)^2 \tag{2}$$

Interpretation of *R(x,y)* can be related to the behavior of α and β as follows:

- When α and β are small, we are in an uniform region.
- if $\alpha > 0$ and $\beta = 0$, the point is an edge.
- if both, α and β, are positive numbers, we have found a corner.

2.2 SUSAN corner detection

SUSAN [9] is a corner detection algorithm based in the analysis of the gradient direction of the intensity in a neighborhood around a point. SUSAN stands for the Smallest Univalue Segment Assimilating Nucleus. The principle of this corner detector is to count all the pixels in a circular neighborhood that have an intensity level similar to the central pixel after smoothing with a Gaussian kernel. This region is named the USAN (Univalue Segment Assimilating Nucleus). When the USAN is composed of all the pixels in the vicinity, the region is uniform.

If the USAN is composed of about 50 % of the total pixels, we are in an edge point. A corner point is present when the USAN only covers less than 25% of the neighborhood.

2.3 Quality requirements for corner detection algorithms

Main requirements for a corner detection algorithm are [10]:

1. All the true corners should be detected.
2. No false corners should be detected.
3. Corner points should be well localized.
4. Corner detector should be robust with respect to noise.
5. Corner detector should be efficient.

Aspects 1 and 2 are evaluated by testing our implementations using widely used benchmark test images (Figure 1). Evaluation of points 3 and 4 is done by performing a stability test for a corner in an image sequence. This sequence presents a quasi-static image perturbed by illumination noise. Point 5 can be satisfied by achieving a real-time frame rate for the corner tracking system.

3 Tests and Results

3.1 Parameter tuning for Harris and SUSAN methods.

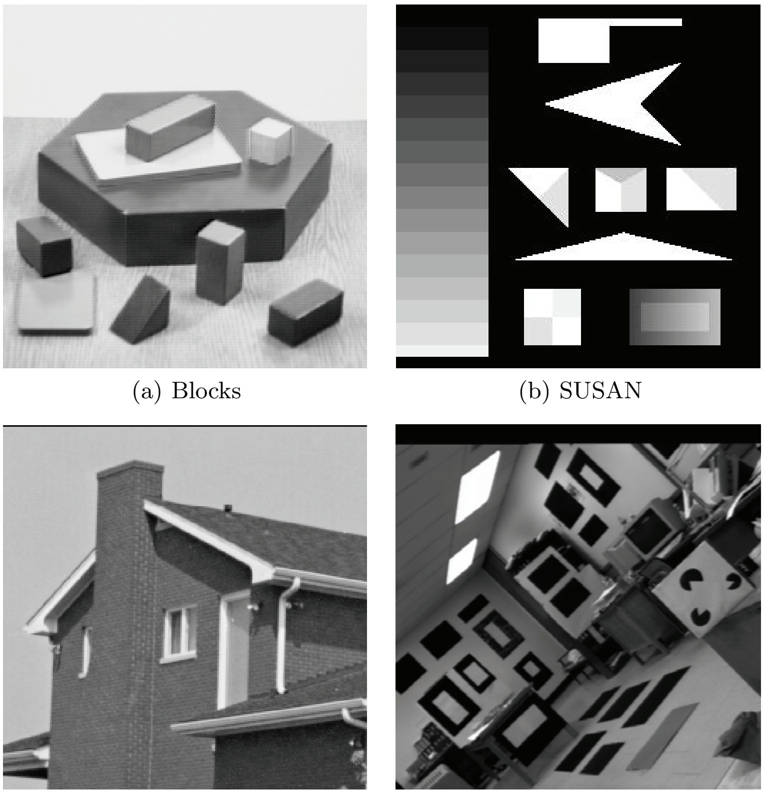
Harris corner detection method is tuned by choosing a variance σ for the Gaussian kernel to be convolved with the intensity Hessian matrix. Best results for the variance parameter of Harris detector when applied to benchmark test images are shown in Table 1.

SUSAN method for corner detection is tuned by adjusting the similarity threshold parameter. This parameter controls the area of the pixels belonging the USAN. Best results for the threshold parameter are also shown in Table 1.

For both methods, a different parameter value is needed for each image. This value is selected by choosing the optimal value of the parameter in order to detect all the corners present in the image. Given the different strengths of the corners, this results in some false corners being detected.

3.2 Test Protocol.

Comparison of corner detectors response to benchmark images Table 1 summarizes the results of the best responses to Harris and SUSAN corner detectors. First column shows to which image (see Figure 1) the detector is applied. Second column shows the actual parameter values used to obtain optimal response. Third column presents the number of corners when the raw algorithm is applies, i.e., no post-processing steps are performed. The results obtained when local minima suppression and thresholding step are shown in fourth column. Graphical results for the SUSAN image when the Harris corner detection



(a) Blocks (b) SUSAN

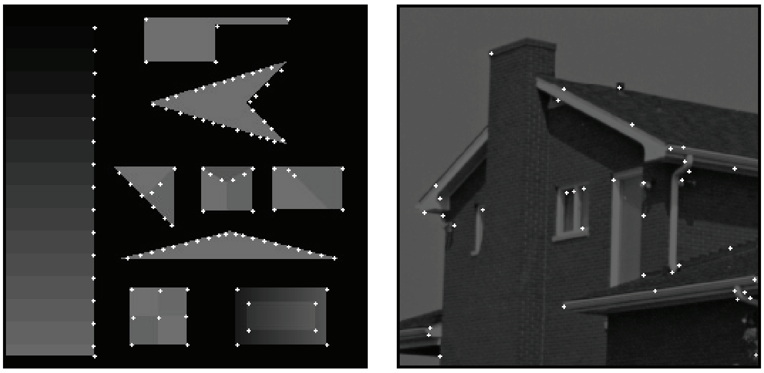
(c) House (d) Lab

Fig. 1. Test images used as benchmarks to tune parameters of the compared corner detection methods.

method is used and House image processed by a SUSAN corner detector are shown in Figure 2. Both images were processed using the optimal parameters shown in Table 1.

We can see that SUSAN detector results in a fewer number of corner points than the Harris method for all the images. However we have also found that Harris works better when corner points come from smoother shapes.

Corner stability for image sequences In the corner stability test, we have applied the corner detection algorithms to a sequence of 1000 frames of a scene with a fixed target. We have recorded the actual coordinate for the corner, and we have recorded also the temporal evolution of the position of the detected corner. We have tested four conditions for both methods: i) without using a correlation step and non controlled illumination, ii) using a correlation step and non controlled illumination, iii) without using a correlation step and non



(a) SUSAN image Harris detector $\sigma = 1.0$ (b) House image SUSAN detector $t = 25$

Fig. 2. Corner detection response for some benchmark test images using optimal parameters.

Image	Detector	Raw Resp.	Refined Resp.
Blocks	Harris, $\sigma = 1.0$	168	111
	SUSAN 36 pixels, t=25.0	65	23
SUSAN	Harris, $\sigma = 0.56$	168	111
	SUSAN 36 pixels, t=25.0	101	36
House	Harris, $\sigma = 1.0$	143	115
	SUSAN 36 pixels, t=25.0	28	19
Lab	Harris, $\sigma = 1.0$	956	802
	SUSAN 36 pixels, t=25.0	268	145

Table 1. Summary of best responses of detectors when applied to benchmark test images.

controlled illumination plus an illumination perturbation, iv) using a correlation step and non controlled illumination plus a perturbation. We summarize the results of these tests in Table 2. For the sake of space we show only the Gaussian fitting of the corner localization error and the temporal evolution for the cases iii) and iv) in Figures 3 and 4 respectively.

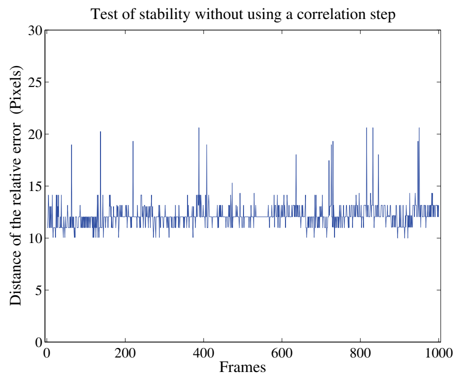
The Gaussian fitting parameters were obtained using the *cftool* provided by Matlab software. Gaussian fitting is of the form:

$$f(x) = a_1 \cdot e^{-\left(\frac{x-\mu}{\sigma}\right)^2} \tag{3}$$

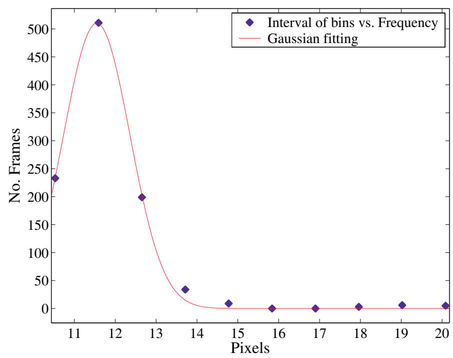
We include also in Table 2 the minimal and maximal errors in corner localization error and the frequency of occurrence along the sequence.

		Gaussian fitting			Minimal error		Maximal error	
Detector	case	μ	σ	a_1	Pixels	Frames	Pixels	Frames
Harris	i	10.17	1.321	516	10	520	20	5
	ii	7.45	0.678	1106	7	900	18	1
	iii	11.55	1.153	510	12	550	20	5
	iv	3.76	1.188	835	3	200	8	30
SUSAN	i	5.06	0.044	995	5	996	6	1
	ii	5.36	0.867	823	5	850	14	10
	iii	3.48	0.242	906	3	900	5	100
	iii	8.79	1.085	708	4	120	10	550

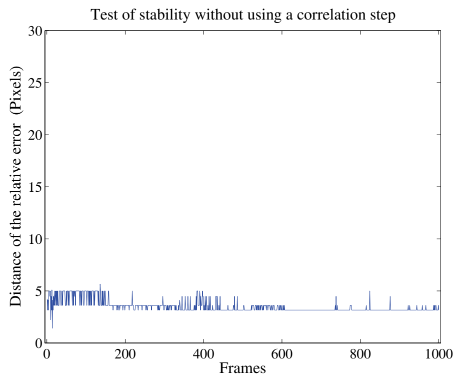
Table 2. Summary of results for the corner stability test.



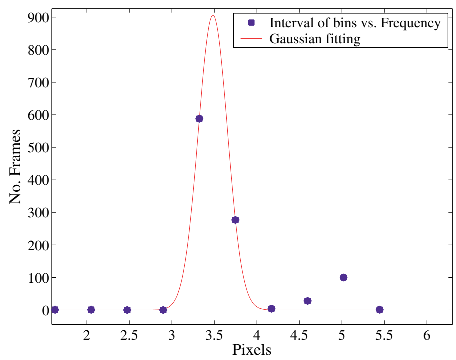
(a) Harris detector temporal evolution.



(b) Harris detector Gaussian fitting.

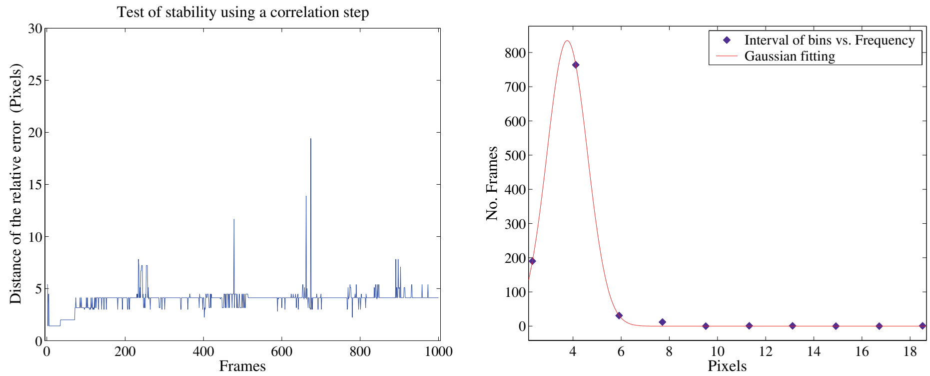


(c) SUSAN algorithm temporal evolution.

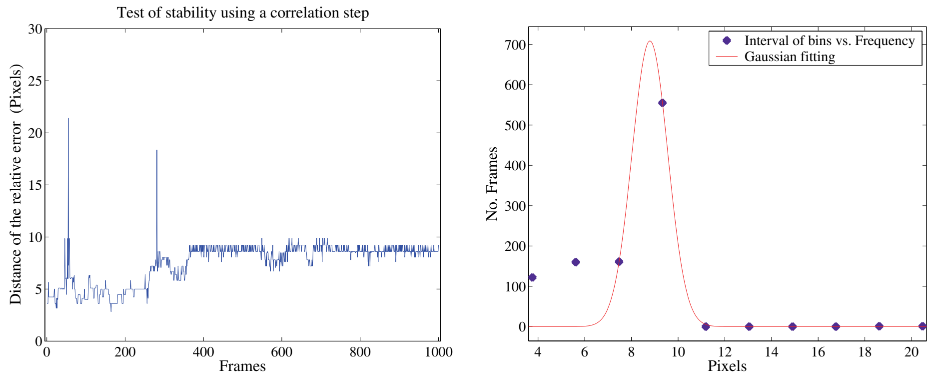


(d) SUSAN algorithm Gaussian fitting

Fig. 3. Corner stability test case iii.



(a) Harris detector temporal evolution. (b) Harris detector Gaussian fitting.



(c) SUSAN algorithm temporal evolution. (d) SUSAN algorithm Gaussian fitting

Fig. 4. Corner stability test case iv.

3.3 Applications

We present in figures 5 and 6, two examples of successful corner tracking applications. Figure 5 presents the tracking of the point of a leaf in an outdoor environment. As we found in previous section, SUSAN method is more robust to illumination changes and in fact, we have obtained better performance with it for this sequence. Figure 6 presents the tracking of the more salient point in a ball that is moved over a textured floor. For this setup, Harris corner detection method has performed better. For both tests, maximal operating frequency was about 8 Hz using a Pentium IV machine running at 2.41 GHz and using 512 MB of RAM.

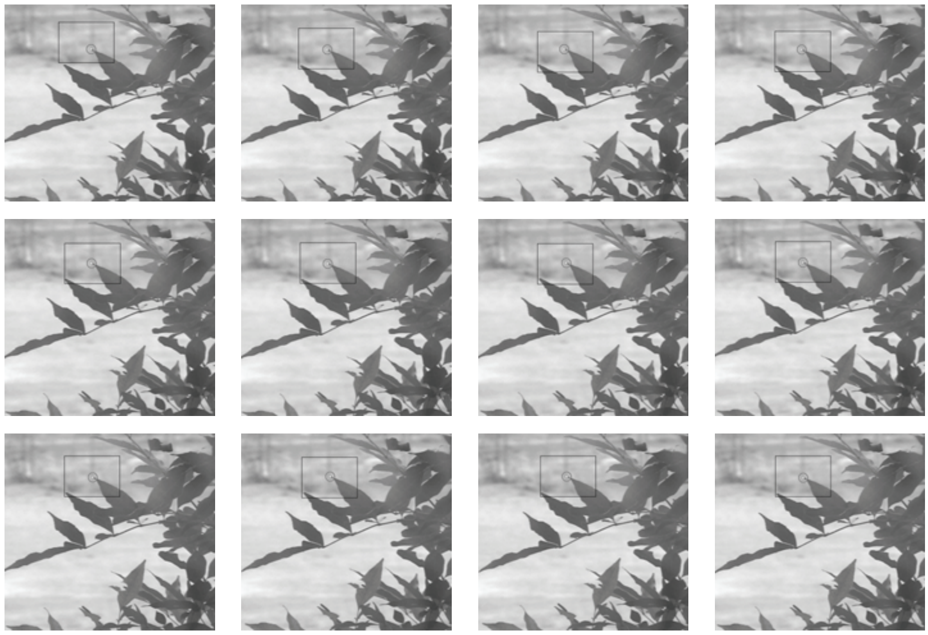


Fig. 5. Some frames of the tracking of the maximal cornerness point on an outdoor image sequence using SUSAN method.

4 Conclusions and Perspectives

We have presented two experiments to evaluate the performance of Harris and SUSAN corner detection algorithms. We have found that SUSAN algorithm yields better results when the scene includes structured objects. Harris corner detector performs better for scenes containing unstructured objects. Nevertheless, SUSAN algorithm has an error under 12 pixels for a corner stability test under varying illumination conditions.

We will work toward inclusion of this tracking module in a robotic platform. More test will be carried out but using images acquired from the robotic vision system. We will also explore its use for the 3D reconstruction of a panoramic stereo vision system.

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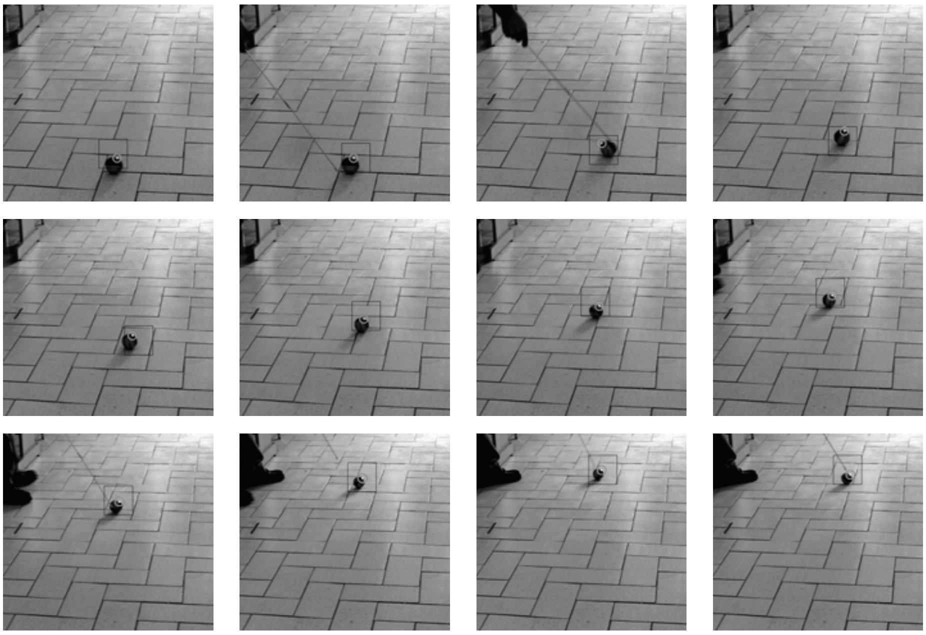

Fig. 6. Some frames of the tracking of the maximal saliency point of an object in a complex indoor environment using Harris corner detection method.

References

1. Brandner, M., Ribo, M., Pinz, A.: State of the art of vision-based self-navigation. In: Proc. 1st Int. Workshop on Robotic Sensing ROSE'03. (2003)
2. Argyros, A.A., Bekris, K.E., Orphanoudakis, S.C.: Robot homing based on corner tracking in a sequence of panoramic images. In: Proc. of the IEEE CSC on Computer Vision and pattern Recognition (CVPR'01). Volume 2., IEEE, Computer Society Press (2001) 3–10
3. Malik, S., McDonald, C., Roth, G.: Hand tracking for interactive pattern-based augmented reality. In: Proc. Int. Symp. on Mixed and Augmented Reality (ISMAR'02). (2002) 117–126
4. Najafi, H., Klinker, G.: Model-based tracking with stereovision for ar. In: Proc. Int. Symp. on Mixed and Augmented Reality (ISMAR'03). (2003) 313–314
5. Skrypnyk, I., Lowe, D.G.: Scene modelling, recognition and tracking with invariant image features. In: Proc. Int. Symp. on Mixed and Augmented Reality (ISMAR'04). (2004) 110–119
6. Beymer, D., McLauchlan, P., Coifman, B., Malik, J.: A real-time computer vision system for measuring traffic parameters. In: Proc. of the 1997 Conf. on Computer Vision and pattern Recognition (CVPR'97). (1997) 495–501
7. Harris, C., Stephens, M.: A combined corner and edge detector. In: Proc. Fourth Alvey Vision Conference. (1988) 147–151
8. Moravec, H.: Towards automatic visual avoidance. In: Proc. Int. Joint Conf. on Artificial Intelligence. (1977) 584

9. Smith, S.M., Brady, J.M.: SUSAN - a new approach to low level image processing. Technical Report TR95SMS1, Defence Research Agency, Franborough, England (1994)
10. Mokhtarian, F., Suomela, R.: Robust image corner detection through curvature scale space. IEEE Trans. on Pattern Analysis and machine Intelligence **20** (1998) 1376–1381