On the Detection and Matching of Structures on Less-textured Scenes

Wan-Lei Zhao[1], Wonmin Byeon[2] and Thomas M. Breuel[2]
[1]*INRIA Rennes, Rennes Cedex, France*
[2]*University of Kaiserslautern, Gottlieb-Daimler-Str, Kaiserslautern, Germany*

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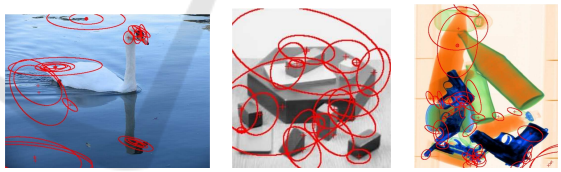
Abstract: Due to the lack of non-zero gradients around the structures in the less textured scenes, current local feature can hardly be applied in less textured object detection. To deal with this issue, two types of local structures, namely, corner and closed region are proposed in this paper. They are based on purely object contours, which are easier to obtain in less textured scenes. Compare to existing detectors, these features describe objects' local structures in a better way. In addition, these new type of local structures also bring the advantage that allows us to have different level of abstraction on the object structures. Its effectiveness has been evaluated under various transformations.

1 INTRODUCTION

Keypoint features have been widely explored in the last decade due to its unique advantages over global features. They have been successfully applied in wide range of applications and systems, such as wide baseline matching (Matas et al., 2002), object retrieval and detection (Sivic and Zisserman, 2003; Lowe, 2004), and near-duplicate image/video detection (Sivic and Zisserman, 2003; Douze et al., 2010). Keypoints have been defined as the local extremas of certain measurement, which ensures their saliency and robustness to various image transformations. In general, one keypoint feature only represents one local structure in an image. It therefore has high chance of coinciding with the canonical structure of an object, which makes it possible to recognize objects by assembling their partial views. Since the keypoint had been introduced, this principle has been successfully adopted in different object detection tasks on the textured images.

Many successes have been reported in different contexts about keypoint features, unfortunately most of the research about keypoint feature detection and application has been concentrating on the texture images. Although the exploration on keypoint feature can be partly attributed to the original search for corners in the less textured objects (Smith and Brady, 1995), few light has been truly shed on how to identify and make use of keypoint features in the less textured contexts. In contrast to the actual world with rich in less textured visual objects, research has not concentrated on the detection of less textured object. Figure 1(a)-(c) show three typical examples of less textured objects. These types of objects are frequently observed in different circumstances. The importance of identifying these objects has been witnessed in recent works (Hinterstoisser et al., 2012; Hinterstoisser et al., 2009; Kim et al., 2007; Mery, 2011). However, the existing detectors are unable to identify the local structures correctly. For instance, as shown in Figure 1(a)-(c), although the Harris-Affine points in Figure 1(a)-(c) are roughly located in the object corners, the characteristic scales estimated for the keypoints are mostly wrong. This is mainly because there are insufficient gradients around the corner. As a consequence, meaningful local structures are no longer desirable in these cases. Compared to object detection in the texture images, due to the lack of suitable features, effective solution is still slow to occur in the less textured cases.



(a) Swan (b) Blox (c) X-ray imaging on Lunggage

Figure 1: Typical examples of less textured objects with Harris-Affine points displayed.

Observing that it is hard to recover the correct local structures on the less textured objects with existing detectors, we propose to identify them based

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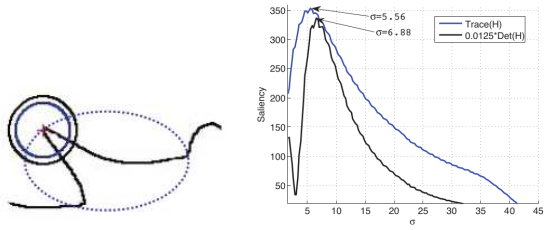
purely on an edge image. By returning back to original way for corner detection, we basically identify two types of local structures, namely corners (also termed as junctions in some cases) and closed regions (visually closed region or blob structures). We observe that these two types of structure already cover most of identifiable local structures of an object. Our approach achieves scale and affine invariances without complicated scale and affine estimation (Mikolajczyk and Schmid, 2004) or simulation (Morel and Yu, 2009). In addition, with the detected structure, we are able to distinguish one compact local patch as background and foreground side. Meanwhile, it also allows to match either between compact local patches or pure object contours.

The remainder of this paper is organized as follows. The related work about keypoint detection and objects detection in less textured images has been reviewed in Section 2. Section 3 details the proposed local structure extraction method in the less textured scene. Section 4 presents the evaluation of proposed keypoint features on standard benchmark in comparison to representative keypoint detectors. Section 5 concludes our findings and overview our future work.

2 RELATED WORK

Corners have been recognized as the most salient and robust structures latent in a visual object. Experiments have shown that removing the corners from images impedes human recognition, while removing most of the straight edge information does not (Tuytelaars and Mikolajczyk, 2008). The general procedure of corner detection involves the localization of corner and the search for the underlying structure around the corner. The latter makes it possible for feature representation and afterwards matching among corners. For edge based methods (Smith and Brady, 1995; Mokhtarian et al., 1998; He and Yung, 2008), most of the research (Smith and Brady, 1995; Mokhtarian et al., 1998; He and Yung, 2008) are limited to localizing the corners, while further exploration on how the complete corner structure can be utilized are left untouched. In contrast, most of the saliency function based approaches (Mikolajczyk and Schmid, 2004; Tuytelaars and Mikolajczyk, 2008) are able to both localize and scale the corner structures. However, these approaches are not suitable for less textured scenes.

As we know, in the saliency function based approaches, the detection of canonical structure of a corner is achieved by automatic scale selection (Linderberg, 1998), usually either *trace* or *determinant* on Hessian matrix is adopted to select characteristic scale in the scale space. In texture images, the detected scales are not expected to perfectly cover corners (Tuytelaars and Mikolajczyk, 2008). Once the structure is functionally salient, the texture field around the structure helps to distinguish it out. However, due to the lack of textures, this doesn't hold for less textured scenes. Figure 2(a) and (b) show a corner structure and its saliency functions in scale space respectively. As shown in Figure 2(b), due to the lack of significant gradient levels, function peaks correspond to visually insignificant scales. While the expected scale (ellipse in dashed line in Figure 2(a)) has been missed. As a result, $Trace(H)$ and $Det(H)$ either produce no meaningful scale (e.g., Figure 1(b) and (c)) or detect multiple characteristic scales around one corner (e.g., Figure 1(c)).



(a) Corner and its characteristic scales

(b) Saliency curves on Corner structure

Figure 2: Corner structure and its scale space saliency curves defined on Hessian matrix (H). The charactertistic scales are found at where *Trace(H)* and *Det(H)* attain their local maxima respectively. The expected scale is illustrated with dashed ellipse in (a).

Besides the risk of missing object true structure in the less textured image, the performance of corner detector can also be affected by complex background on which the object lies. In general, corners are often found near object boundaries as this is where the intensity change usually occurs. The region extraction process is often based on measurements on non-planar structures, e.g., including background or another facet of the object (Tuytelaars and Mikolajczyk, 2008). In these cases, the robustness to background changes will be affected for most of existing detectors (Tuytelaars and Mikolajczyk, 2008).

In (Pantofaru et al., 2006), region based context feature is proposed to cope with the less textured objects. It models the relationship between closed regions and identify spatial proximity among object features. It aims to capture the object shapes and their discriminative surface. However, it is still difficult to obtain reliable feature regions and proper structure of the object due to unstable segmentations.

3 EDGE BASED DETECTION OF LOCAL STRUCTURES ON LESS TEXTURED OBJECT

3.1 Pre-processing

The procedure of keypoint extraction begins with the edge detection. Canny edge detection algorithm (John, 1986) is first applied on the input image. The choice of Canny edge detection is mainly due to its simplicity and stability in different situations. In order to ensure the detected edge is exactly one pixel wide, the edge detection results are further processed with thinning algorithm proposed in (Zhang and Wang, 1996). Followed by the thinning, the bitmap of edges has been parsed into graph representation. In the graph representation, we maintain the original connectivity and sequential orders of the pixels along the edges. After this pre-processing, each disconnected contour is ready and will be treated independently for local structure detection in the later stages.

3.2 Corner Detection

There are several ways available for corner detection along object contours (Mokhtarian et al., 1998; Nakagawa and Rosenfeld, 1979; Liu et al., 2009; He and Yung, 2008). Most of the approaches define corners on the local maximum of the edge curvature. After a comparative study over the effectiveness of different definitions about the curvature, we adopt approach presented in (Nakagawa and Rosenfeld, 1979). According to (Nakagawa and Rosenfeld, 1979), the curvature in edge pixel $P(x,y)$ can be defined as

$$\theta = |arctan(\frac{y_2 - y_1}{x_2 - x_1})|, \quad (1)$$

where $P_b(x_1,y_1)$ and $P_f(x_2,y_2)$ are points W_0 pixels before and after the current pixel P respectively along the edge. W_0 is empirically set to *7* and kept the same across all our experiments in the paper. With the help of Eqn. 1, curvature of each pixel along the edge can be sequentially calculated and kept in order. Then this curvature sequence has been undergone several runs of linear smoothing. Followed by the smoothing, the corner detection starts from either ends of the edge segment. The edge points are recognized as corners when they attain the local maximum on Eqn. 1. Since each disconnected edge is treated separately, process above has been repeated on each edge curve.

As observed in Figure 3(b), the detected corner point (e.g., c_1, c_2 or c_3) carries very limited information if we view them alone. As a matter of fact, it is the curved structure centering on the corner (e.g., curve $\widehat{c_1c_2}$ and $\widehat{c_2c_3}$ in Figure 3(b)) distinguishes the corner (e.g., c_2 in Figure 3) out. Based on this observation, we integrate two neighboring segments with the corner as a uniform local structure. This time the corners we discovered are the local curved structures. For each corner structure, the concave side can be approximated by an inscribed triangle which connects the three consecutive corners (e.g., c_1, c_2 and c_3 in Figure 3(b)). Furthermore, the affine region over this local structure can be approximated by a circumscribed ellipse of this triangle. The ellipse is known as *Steiner ellipse* (Kimberling and Hofstadter, 1998) which is defined in Eqn. 2.

$$a(x-x_0)^2 + b(x-x_0)\cdot(y-y_0) + c(y-y_0)^2 = 1, \quad (2)$$

where

$$x_0 = \frac{x_1+x_2+x_3}{3}, \quad y_0 = \frac{y_1+y_2+y_3}{3}$$

Additionally, we define matrix B as

$$B = \begin{bmatrix} (x_1-x_0)^2 & (x_1-x_0)\cdot(y_1-y_0) & (y_1-y_0)^2 \\ (x_2-x_0)^2 & (x_2-x_0)\cdot(y_2-y_0) & (y_2-y_0)^2 \\ (x_3-x_0)^2 & (x_3-x_0)\cdot(y_3-y_0) & (y_3-y_0)^2 \end{bmatrix}, \quad (3)$$

and B_i ($i = 1,2,3$), which shares all the elements with B except that the ith column has been replaced by $(1,1,1)^T$. The parameters in Eqn. 2: a, b and c can be determined by Eqn. 4.

$$a = \frac{Det(B_1)}{Det(B)}, b = \frac{Det(B_2)}{Det(B)}, c = \frac{Det(B_3)}{Det(B)}, \quad (4)$$

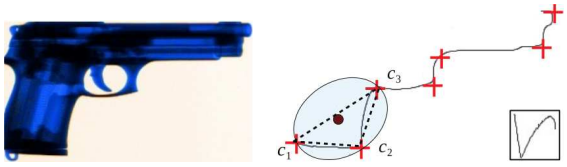
where $Det(\cdot)$ is the determinant of a matrix. Up-to-now, the corner structure has been approximated by an affine region. The affine invariance now becomes achievable if we assume this affine region has been transformed from a structure norm by linear transformation based on Eqn. 5.

$$T = \begin{bmatrix} a & b/2 & 0 \\ b/2 & c & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (5)$$

Figure 3 demonstrates the process of corner detection and affine region approximation. Especially, the detected local structure that has been normalized by the T^{-1} is shown in bottom right of Figure 3(b).

3.3 Closed Region Detection

Although in the edge image, salient structures of an object can be largely decomposed into corners, there is still another type of local structure we fail to cover. For example, no corner will be detected on a circle



(a) X-ray imaging on a handgun (b) Detect corners on an edge from (a)

Figure 3: Corners detection on Canny edge of input image.

since the curvatures along the edge are constant. In other cases, corners can be detected while we still miss the local structure as a whole, since corners are overheadly decomposed. Intuitively the more complicated the local structure is, the more distinguishable it is. As a result, detecting this type of local structure which has been missed in corner detection is also expected.

Observing that these local structures appear as closed curve with arbitrary shapes in the edge image. Our algorithm only considers edge segment open on one side. In the case that the expected closed segment has been broken in several ways, we believe they can still be roughly approximated by corners individually.

The problem of detecting closed (or semi-closed) curve region can be generalized into a traditional shortest path searching between any two end-points in the connected edge segments. The end-point refers to either end-point of a segment or a junction at which more than one segment joins with each other. They are treated as vertex in a graph representation. Similarly, the segment which connects two end-points is treated as an edge in between two vertices. The edge weight is consequently assigned to the length of the segment. Shortest path searching is therefore exhaustively undertaken for all the end point pairs. Since we have limited number of vertices in the graph, the detection can be fulfilled efficiently.

As noticed before, the closed region R would be in an arbitrary shape and orientation. As a result, direct matching of one closed region with its linearly transformed counterpart involves probing the whole transformation space (anisotropic scaling and rotation), which is in prohibitively high cost. To handle this issue, similar to corner detection, we superimpose an approximated affine region on the detected closed (or nearly closed) structure. This is done by collecting all the points which fall inside the region. Such that the covariance matrix in Eqn. 6 defined on these points regularizes an ellipse centering on the region center $\mu(R)$.

$$\Sigma(R) = \frac{1}{|R|}\sum_{x\in R}(x-\mu)(x-\mu)^T, \qquad (6)$$

(a) Canny edge from Figure 1(b) (b) Corners found on (a) (c) Closed Regions found on (a)

Figure 4: Corners and closed regions detected from input edge image.

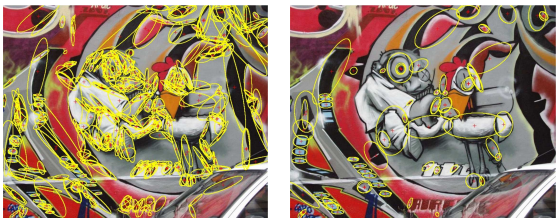
where

$$\mu(R) = \frac{1}{|R|}\sum_{x\in R} x. \qquad (7)$$

Similar to corner structure, with the help of the affine adaptation, the detected closed region can be normalized. Visually relevant regions which have been affinely transformed become comparable once being normalized with their $\Sigma^{-1}(R)$s respectively.

3.4 Detect Local Structure in Multiple Scales

Traditionally, the purpose of detecting keypoints in multiple scales is to select a proper characteristic scale on which the saliency function attains local extrema. Similar local structures will coincide on similar characteristic scales, such that the local structures with different scaling are comparable to each other. Thus, scale invariance is achieved. In our case, both the corner and closed region maintain the same shape under arbitrary isotropic scaling. Once normalizing the local structure into fixed-size patch (e.g., 41×41 in SIFT (Lowe, 2004)), scale invariance is achievable. However, according to scale space theory (Linderberg, 1998), the purpose of detecting keypoints in multiple scales in its nature is to simulate the vision effect of viewing objects from different distances. In our case, object contour varies when it has been observed from different distances. Edge detection under different scales may generate different object contours and this in turn results in different local structures. As a consequence, detecting corners and closed region in multiple scales could help us to identify different local structures as much as possible. More importantly, if a group of local structures are repeatedly observed that are located in the same contour, the layout of object parts can be captured. As a result, detecting local structures in multiple scale also helps us to relate local stuctures according to object layout. In the implementation, the scale space is simulated by varying σ_k increasingly ($\sigma_k = k\cdot\sigma_0, k = 1,2,...$) while the '*low*' and '*high*' thresholds are fixed to *0.15* and



(a) Corners (b) Closed Regions

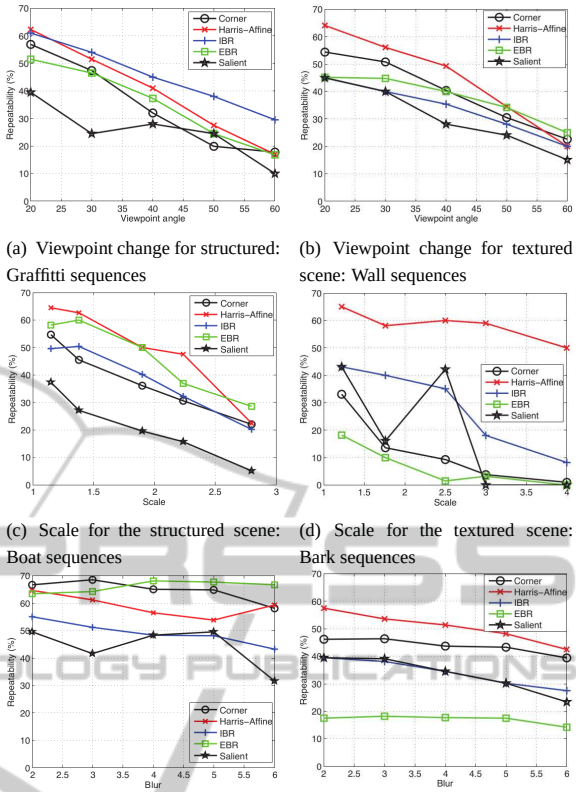
Figure 5: Local structures detected (6 scales and 3 octaves) on the first image of Graffiti sequence.

0.75 respectively. To ensure the stableness of detected structures, only structures appear in at least two consecutive scales are kept. In addition, similar to (Lowe, 2004), it is no need to keep the image in its original size when σ_k is considerably high. The scale space is actually simulated by three octaves. In each octave, four scales with increasing σ_k are generated.

4 OBJECTS RECOGNITION IN LESS-TEXTURED AND TEXTURE RICH SCENES

The experiments in this section investigate the effectiveness of the proposed local feature against different transformations under object recognition task. In order to have a clear picture about its suitability in different contexts, the experiments are conducted on both textured and structured (less textured) images. Similar to (Mikolajczyk et al., 2005), we investigate the repeatability score of the proposed detector (denoted as '*corner*') in comparison to popular detectors which achieve scale and affine invariance. They are namely Harris-Affine (Mikolajczyk and Schmid, 2004) based on saliency function, IBR (Tuytelaars and Gool, 1999) and EBR (Turina et al., 2001) which are based on image edges, and Salient region (Kadir et al., 2004) that is based on image intensity levels. The following experiment is conducted based on the image sequences and testing software provided by K. Mikolajczyk (Mikolajczyk and Schmid, 2005). The transformations incorporated in these image sequences range from viewpoint changes, scaling and rotation to different levels of blur. In each transformation type, detectors are tested with both structured and textured scenes. Detected corners and closed regions on 'Graffitti' image are shown in Figure 5. For the structures extracted by other detectors (Harris-Affine, IBR, EBR and Salient region), please refer to (Mikolajczyk et al., 2005).

As shown in Figure 6, Harris-Affine overall outperforms other detectors, while Salient region are in-



(a) Viewpoint change for structured: Graffitti sequences

(b) Viewpoint change for textured scene: Wall sequences

(c) Scale for the structured scene: Boat sequences

(d) Scale for the textured scene: Bark sequences

(e) Blur for the structured scene: Bikes sequences

(f) Blur for the textured scene: Trees sequences

Figure 6: Repeatability of Local structures in comparison to popular keypoint detectors under different transformations.

effective in most of the cases. Compared to the performances in structured scenes, all edge based approaches (corner, IBR and EBR) suffer considerable performance drops under the scenes that are full of textures. The instability of these approaches is mainly due to the low reliability of edge detection in textured scene. However, if we consider these structured scenes only, the proposed approach demonstrates more stable performances than others in less textured scenes. This implies our approach is rather suitable on structured (shown in figures on the left column) than the textured cases. Although Harris-Affine demonstrates stable performance in terms of repeatability, due to the reason explained in Section 2, it is not really promising for less textured scene, which will be verified in our second experiment.

5 CONCLUSIONS

We have presented our approach on extracting salient local structures, namely corners and closed regions, in less textured scenes. As illustrated in the paper,

these features can be easily adapted with the local object structures and demonstrate stable performances in less textured scenes. Moreover, as they are derived from object contours, these structures have the flexibility of allowing different levels of abstraction on the descriptors. To alleviate the instability of image contour detection and apply this feature extraction on different object types are the directions to explore in the future.

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REFERENCES

Douze, M., Jégou, H., and Schmid, C. (2010). An image-based approach to video copy detection with spatio-temporal post-filtering. *IEEE Transactions on Multimedia*, 12(4):257–266.

He, X. C. and Yung, N. H. C. (2008). Corner detector based on global and local curvature properties. *Optical Engineering*, 47(5).

Hinterstoisser, S., Cagniart, C., Ilic, S., Sturm, P., Navab, N., Fua, P., and Lepetit, V. (2012). Gradient response maps for real-time detection of texture-less objects. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 34(5):876–888.

Hinterstoisser, S., Kutter, O., Navab, N., Fua, P., and Lepetit, V. (2009). Real-time learning of accurate patch rectification. pages 2945–2952.

John, C. (1986). A computational approach to edge detection. *IEEE Transactions on Pattern Analysis Machine Intelligence*, 8(6):679–698.

Kadir, T., Zisserman, A., and Brady, M. (2004). An affine invariant salient region detector. In *In Proceedings of the 8th European Conference on Computer Vision*, pages 345–457.

Kim, G., Hebert, M., and Park, S.-K. (2007). Preliminary development of a line feature-based object recognition system for textureless indoor objects. *Recent Progress in Robotics: Viable Robotic Service to Human*.

Kimberling, C. and Hofstadter, D. (1998). *Triangle centers and central triangles*. Number 129 in Congressus numerantium. University of Manitoba.

Linderberg (1998). Feature detection with automatic scale selection. *International Journal of Computer Vision*, 30(2):79–116.

Liu, J., Jakas, A., AI-Obaidi, A., and Liu, Y. (2009). A comparative study of different corner detection methods. In *IEEE International conference on Computational intelligence in robotics and automation*, pages 509–514.

Lowe, D. (2004). Distinctive image features from scale-invariant keypoints. *International Journal on Computer Vision*, 60(2):91–110.

Matas, J., Chum, O., Urban, M., and et. al (2002). Robust wide baseline stereo from maximally stable extremal regions. In *British Machine Vision Conference*, pages 384–393.

Mery, D. (2011). Automated detection in complex objects using a tracking algorithm in multiple x-ray views. In *IEEE Workshop on Object Tracking and Classification Beyond the Visible Spectrum in Conjunction with Computer Vision and Pattern Recognition*, pages 41–48.

Mikolajczyk, K. and Schmid, C. (2004). Scale and affine invariant interest point detectors. *International Journal of Computer Vision*, 60:63–86.

Mikolajczyk, K. and Schmid, C. (2005). A performance evaluation of local descriptors. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 27(10):1615–1630.

Mikolajczyk, K., Tuytelaars, T., Schmid, C., Zisserman, A., Matas, J., Schaffalitzky, F., Kadir, T., and Gool, L. V. (2005). A comparison of affine region detectors. *International Journal of Computer Vision*, 65(1-2):43–72.

Mokhtarian, Farzin, and Suomela, R. (1998). Robust image corner detection through curvature scale space. *IEEE Transactions on Pattern Analysis Machine Intelligence*, 20(12):1376–1381.

Morel, J.-M. and Yu, G. (2009). ASIFT: A new framework for fully affine invariant image comparison. *SIAM Journal on Imaging Sciences*, 2(2):438–469.

Nakagawa, Y. and Rosenfeld, A. (1979). A note on polygonal and elliptical approximation of mechanical parts. *Pattern Recognition*, 11:133–142.

Pantofaru, C., Dorko, G., Schmid, C., and Hebert, M. (2006). Combining regions and patches for object class localization. pages 23–30.

Sivic, J. and Zisserman, A. (2003). Video google: A text retrieval approach to object matching in videos. In *IEEE International Conference on Computer Vision*, pages 1470–1477.

Smith, S. M. and Brady, J. M. (1995). Susan - a new approach to low level image processing. *International Journal of Computer Vision*, 23:45–78.

Turina, A., Tuytelaars, T., and Gool, L. V. (2001). Efficient grouping under perspective skew. In *IEEE International Conference on Computer Vision and Pattern Recognition*.

Tuytelaars, T. and Gool, L. V. (1999). Content-based image retrieval based on local affinely invariant regions. In *In International Conference on Visual Information Systems*, pages 493–500.

Tuytelaars, T. and Mikolajczyk, K. (2008). *Local Invariant Feature Detectors: A Survey*. Now Publishers Inc., Hanover, MA, USA.

Zhang, Y. Y. and Wang, P. S. P. (1996). A parallel thinning algorithm with two-subiteration that generates one-pixel-wide skeletons. In *IEEE International Conference on Pattern Recognition*, pages 457–461.