

On the Detection and Matching of Local Structures on Less Textured Objects

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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 cleaner and easier to obtain in less textured scenes. Compared to existing detectors, they adapt to object local structures better. 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 image transformations and has been demonstrated with object detection in X-ray images.

1 INTRODUCTION

Image local features (also known as keypoints) have been widely explored in the last decades 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 extrema 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. Due to the introduction of keypoint, 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 few research on the detection of less textured object, our world is actually rich in less textured visual objects. Figure 1(a)-(c) show three typical examples of less tex-

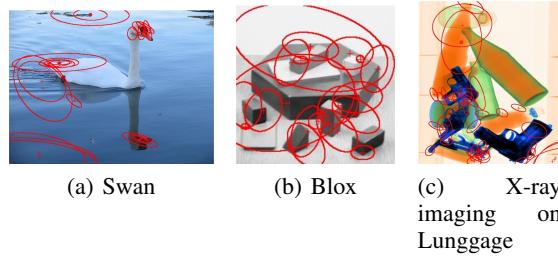


Figure 1: Typical examples of less textured objects with Harris-Affine points displayed.

tured objects. These types of objects are frequently observed in different circumstances. The importance of identifying these objects has been witnessed in recent works (Hinterstoesser et al., 2012; Hinterstoesser 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 less textured cases. Observing that it is hard to recover the correct local structures on the less textured objects with existing saliency structure detectors, we propose to identify them based purely on 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. Compared to existing ways on achieving scale and affine invariance (Mikolajczyk and Schmid, 2004), 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 matching 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 less textured scene. Section 4 introduces our way of feature representation for less textured local patches. Section 5 presents the evaluation of proposed keypoint features on standard benchmark in comparison to representative keypoint detectors. In addition, suspicious object detection in X-ray images is demonstrated. Section 7 concludes our findings.

2 Related Work

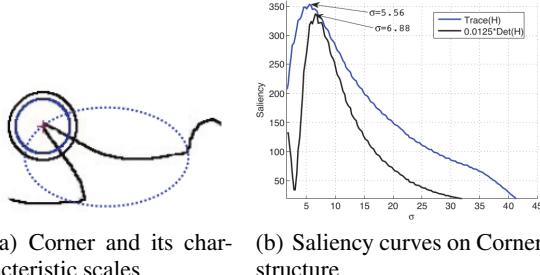
Corners have been recognized as the most salient and robust structures latent in a visual object. Experiments have shown that removing the corners from images impedes human recognition, while removing most of the straight edge information does not (Tuytelaars and Mikolajczyk, 2008). The general procedure 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 revealed and 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 selec-

tion (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, $\text{Trace}(H)$ and $\text{Det}(H)$ 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)). 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 in 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). As noticed in Figure 1, apart from less textured real objects, X-ray images are another major image source, in which texture can hardly be observed. Object detection in X-ray has been left largely unexplored although it could be pretty helpful in automatically discovering suspicious objects in airports, customs and etc. Compared to object detection in the less textured natural image, transparency phenomenon makes the task even tougher. Due to the inherent difficulties, few efforts have been made on automatic object detection in X-ray images. Available work (Mery, 2011) focuses on how to integrate multiple views of X-ray scanning. However, this work is limited to localizing instead of recognizing objects.

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 algo-



(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 characteristic scales are found at where $\text{Trace}(H)$ and $\text{Det}(H)$ attain their local maxima respectively. The expected scale is illustrated with dashed ellipse in (a).

rithm (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. Notice that, this pre-processing has no preference on edge detection algorithms. However, good edge detection algorithm will necessarily boost the overall performance.

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; ?). Approaches presented in these works, although different in details, most of them 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

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

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. To alleviate the effect of noises, 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 is 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 $\widehat{c_1 c_2}$ and $\widehat{c_2 c_3}$ 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 the i th column has been replaced by $(1, 1, 1)^T$. The parameters in Eqn. 2: a , b and c can be determined by Eqn. 4.

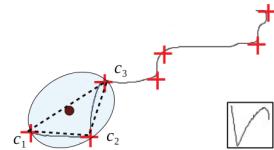
$$a = \frac{\text{Det}(B_1)}{\text{Det}(B)}, b = \frac{\text{Det}(B_2)}{\text{Det}(B)}, c = \frac{\text{Det}(B_3)}{\text{Det}(B)}, \quad (4)$$

where $\text{Det}(\cdot)$ is the determinant of a matrix. Up-to-now, the corner structure has been approximated by an affine region. Similar to affine estimation approach presented in (Mikolajczyk and Schmid, 2004), 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.

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



(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. 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 may fail to cover. For example, no corner will be detected on a circle since the curvatures along the edge remain constant. In other cases, corners can be detected while we still miss the local structure as a whole, since corners are overheadly decomposed in this case. Intuitively the more complicate 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. The task of detecting these local structures is to identify the closed curves among edges. However, as more frequently observed in practice, due to the noises and inaccuracy of edge detection, these curves may be broken at some points. For this reason, on one hand, one cannot simply parse through pixels along each edge and check whether one end of the edge segment is exactly connected to another. On the other hand, if the expected closed structure has been broken into several edge segments, the visual meaning of the structure can be interpreted in various ways. To precisely understand and identify these types of structure requires either the intervention of human being or training, which is out of the scope of this paper. As a result, 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 one segment or a junction at which more than one segments join with each other. They are treated as vertex in a graph representation. Similarly, the segment

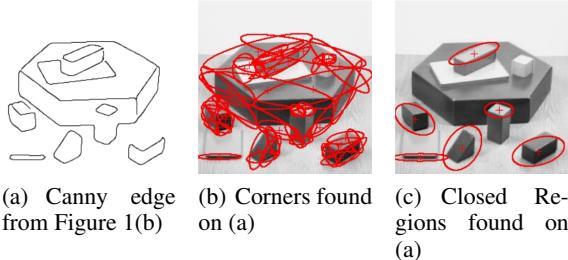


Figure 4: Corners and closed regions detected from input edge image.

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 one 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 $\mu(R)$.

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

where

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

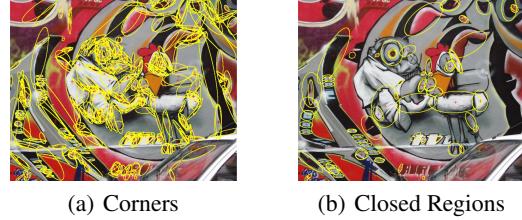
Similar to corner structure, with the help of the affine adaptation, the detected closed region can be normalized. Visually relevant regions which have been affinely transformed become comparable once being normalized with their $\Sigma^{-1}(R)$'s respectively.

Comments As demonstrated in Figure 4, corners and closed region capture different local structures, comparing with Figure 1(b), these two types of corner adapt to the object structures better. Comparing with traditional detectors, both corners and closed regions allow different levels of abstraction on the local structure. In practice, when we are asked to judge whether two portraits are from the same person, we compare whether the photos are identical on pixel level. While if we are asked to tell whether goose and duck are birds, only shape matters according to our vision. Unfortunately, far less powerful than human vision, descriptor cannot achieve different levels of abstraction

within one feature, different types of descriptor are thus required in different applications. We are now enabled with three choices. Firstly, as other keypoint detection approaches, we can take the whole local patch covered by the ellipse. Alternatively, we can also divide the local patch into background and foreground. Each detected structure is acted as dividing boundary. Further more, object or its parts can be also represented with the contours solely (as shown in Figure 3(b)).

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 become comparable to each other. Thus, scale invariance is achieved. In our case, both the corner and closed region maintain the same shape when 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 (Lindberg, 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 ($\sigma_k = k \cdot \sigma_0, k = 1, 2, \dots$) while the ‘low’ and ‘high’ thresholds are fixed to 0.15 and 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.



(a) Corners

(b) Closed Regions

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

4 Experiment

4.1 Experiment-I: Performance Evaluation in Objects rich in textures

Our first experiment investigates the robustness of the proposed local feature against different transformations. In particular, 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 ‘Graffiti’ 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 ineffective 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 across all transformations we considered so far.

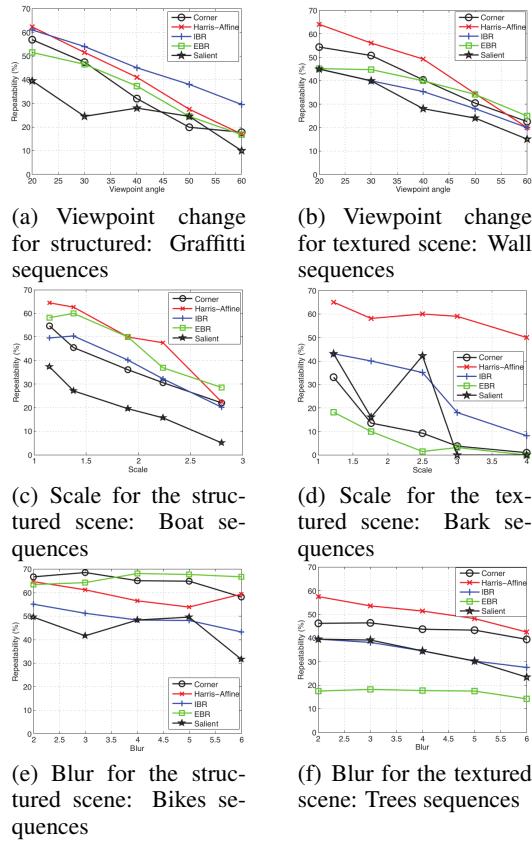


Figure 6: Repeatability of Local structures in comparison to popular keypoint detectors under different transformations.

This implies our approach is rather suitable on structured (less textured scenes) 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.

4.2 Experiment-II: Object Detection in X-ray image

In this experiment, we demonstrate the effectiveness of proposed method with object detection task in X-ray images. The X-ray images are recorded on a dual-energy X-ray machine, which provides 4 views (one from top, one from side and two views at some angle) for each baggage. In the experiment, we match suspicious object template to image of scanned baggages that are mixed with different materials such as clothes, shoes, bottles, mobile phones. The performance of proposed local structures has been compared with Harris-Affine. Both the normalized curve structures and Harris-Affine patches are represented

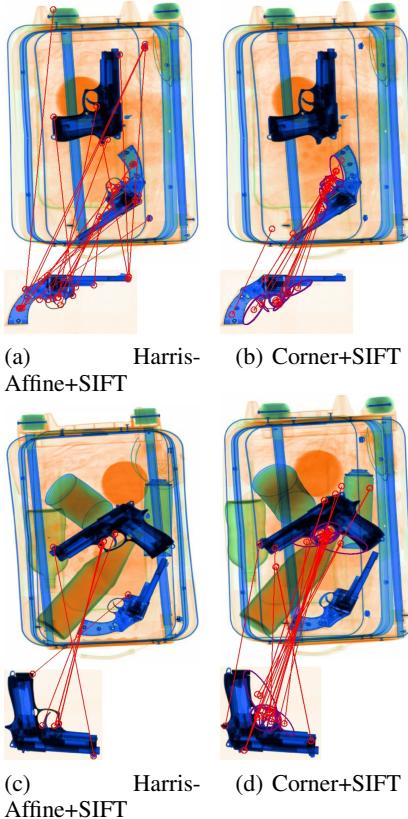


Figure 7: Point-to-point matching for Harris-Affine points and local structures. Correctly matched structures in (b) and (d) are highlighted with ellipses.

with SIFT. In the matching with ‘corners’, corners are put into one group if they are located in the same contour. As a result, object layouts information are considered. It restricts matching to take place between groups thus avoids potential false matches. In contrast, it is impossible to impose such kind of layout constraint for local features such as Harris-Affine points. Figure 7 shows the point-to-point matching results between object template and scanned baggages. As seen in the figure, without further geometric verification, our proposed feature produces more number of coherent matches. While Harris-Affine feature suffer from either indistinctive local structures (Figure 7(a)) or background noises (Figure 7(c)).

5 Conclusion

We have presented our approach on extracting salient local structures, namely corners and closed regions, from the less textured scenes. As illustrated, they are able to adapt to the local object structures well and demonstrate stable performances in less tex-

tured scenes. Specifically, the detected local structure has been applied in suspicious object detection in X-ray images. Encouraging results are also achieved. Moreover, as they are derived from object contours, these types of structures also offer 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 other object types are the potential directions to explore in the future.

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If any, should be placed before the references section without numbering. To do so please use the following command: \section*{ACKNOWLEDGEMENTS}

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