Localization of Saliency through Iterative Voting

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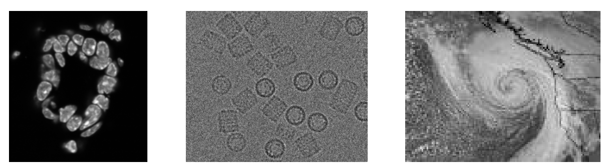
Abstract

Saliency is an important perceptual cue that occurs at different scales of resolution. Important attributes of saliency are symmetry, continuity, and closure. Detection of these attributes is often hindered by noise, variation in scale, and incomplete information. An iterative voting method using oriented kernels is introduced for inferring saliency as it relates to symmetry or continuity. A unique aspect of the technique is in the kernel topography, which is refined and reoriented iteratively. The technique can cluster and group nonconvex perceptual circular symmetries along the radial line or sparse features along the trangential direction. It has an excellent noise immunity, and is shown to be tolerant to perturbation in scale. Applications of this approach to blobs with incomplete and noisy boundaries and to scientific images are demonstrated.

1 Introduction

Saliency is an important perceptual cue for feature-based representation, fixation, and description of large-scale datasets. Saliency can be driven by continuity, symmetry, or closure. Among these, it is well known that symmetry is a preattentive process [1] that improves recognition, provides an efficient mechanism for scene representation, and aids in reconstruction and description. Radial symmetry is a special class of symmetry, which persists in nature at multiple scales. Robust and efficient detection of inexact radial symmetries facilitates semantic representation of images for summarization and interpretation. Examples include the shape of a nucleus, organization of nuclei in tissue observed with an epi-fluorescence microscope, oceanic vortices imaged through observational platforms or numerical simulation models of fluid flow, and general blob detection. At the lowest level, a radial symmetry operator can be used as an interest operator for detecting critical features that lead, for example, toward visual attention. However, interest operators have to be fast, retain good noise immunity, be sufficiently stable with respect to the underlying intensity distribution, and be capable of delineating/resolving nearby features into disjoint events. Yet, the notion of radial symmetry is used in a weak sense since the basic geometry can deviate from convexity and strict symmetry for inferring the center of mass. The proposed method allows inference of the center of mass from incomplete boundary information through voting and perceptual grouping, and is implemented through refinement of specifically tuned voting kernels. Figure 1 shows several examples indicating potential application areas.



(a) (b) (c)

Figure 1: Radial symmetries in scientific applications: (a) position of nuclei in tissue; (b) macromolecular assemblies imaged through cryo-electron microscopy; (c) vortex formation in atmospheric data.

Spatial voting has been studied for at least four decades. Hough introduced the notion of parametric clustering in terms of well-defined geometry, which was later extended to the generalized Hough transform. In general, voting operates on the notion of continuity and proximity, which can occur at multiple scales, e.g., points, lines, lines of symmetry, or generalized cylinders. The novelty of our approach is in defining a series of kernels that vote iteratively along the radial or tangential directions. Voting along radial direction leads to localization of the center of mass, while voting along the tangential direction advances continuity. At each iteration, kernel orientation is refined until it converges to a single focal response. Several different varia-

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tions of these kernels have been designed and tested. They are cone-shaped, have a specific scale and spread, and target geometric features of approximately known dimensions. In the case of radial symmetry, the voting kernels are applied along the gradient direction, then at each consecutive iteration and at each grid location, their orientation is aligned along the maximum response of the voting space. The shape of the kernel is also refined and focused as the iterative process continues. The method is applicable to perceptual shape features, has excellent noise immunity, is tolerant to variations in target shape scale, and is applicable to a large class of application domains.

The organization of this paper is as follows. Section 2 provides a brief review of the previous research. Section 3 describes the basic idea and detailed implementation of evolutionary voting. Section 4 demonstrates the experimental results. Section 5 concludes the paper.

2 Review of previous work

Complexities in the detection of saliency are often due to variations in scale, noise, and topology. Other complexities originate from missing data and perceptual boundaries that lead to diffusion and dispersion of the spatial grouping in the object space. Techniques in radial symmetries can be classified into three different categories: (1) point operations leading to dense output, (2) clustering based on parameterized shape model or voting, and (3) iterative techniques. Point operations are usually a series of cascade filters that are tuned for radial symmetries [2]. These techniques use image gradient and orientation to infer center of mass for blobs of interest [5, 6, 7]. Recent efforts [2] have focused on speed and reliability. Parametric clustering techniques are often based on a variant of the Hough transform, e.g., circle or ellipse finder. These techniques produce loci of points corresponding to the parametric models of well-known geometries. These point distributions are then merged, and model parameters are refined. Non-parametric clustering techniques operate along the gradient direction to search for radial symmetry, which could be line- or area-based. Line-based search [4] is also known as spoke filter, where the frequency of occurrence of points normal to the edge direction are aggregated. In contrast, area-based voting accumulates votes in a small neighborhood along the gradient direction. Examples of iterative methods include watershed [8] and regularized centroid transform (RCT) [9], which transport boundary points to the local center of mass iteratively. These can be classified as curve-based voting since the voting path is not along a straight line but along a minimum energy path. Voting paths can be easily distorted by noise, local structures, and other singularities in the image, and may lead to over-segmentation. Thus, the solution needs to be regularized.

In summary, interest-point operators are fast and well-suited for detecting small features for higher levels of interpretation and manipulation. Parametric voting techniques could be memory intensive depending upon the dimensionality of the parameter space and remain sensitive to small deviations from the underlying geometric model. Line- and area-based voting produce a voting space that is diffused and subject to further ad hoc analysis. On the other hand, iterative techniques are adaptive to geometric perturbation and produce more stable results. The proposed method shares some attributes with tensor-based voting [3], however, it differs in that it is iterative, can be model-based, and is scalar. It demonstrates excellent performance in the presence of noise, variations in scale, and topological changes.

3 Approach

Let (1) $I(x, y), (x, y) \in D$ be the original image; (2) $\alpha(x, y)$ be the voting direction where $\alpha(x, y) := (\cos\theta(x, y), \sin\theta(x, y))$; (3) $r_{\min}, r_{\max}$ be the radial range; and (4) A be the voting area defined by

$$A(x, y; r_{\min}, r_{\max}, \Delta) := \{(x \pm r\cos\phi, y \pm r\sin\phi) \\ | r_{\min} \leq r \leq r_{\max}, \theta(x, y) - \Delta \leq \phi \leq \theta(x, y) + \Delta\} \tag{1}$$

and (5) voted image with parameters $(r_{\min}, r_{\max}, \Delta)$ be denoted by $V(x, y; r_{\min}, r_{\max}, \Delta)$.
The voting method is as follows:

Iterative Voting

0) *Initialize the parameters:* $r_{\min}, r_{\max}, \Delta_{\max}$ and a sequence $\Delta_{\max} = \Delta_N < \Delta_{N-1} < \cdots < \Delta_0 = 0$. And set $n := N, \Delta = \Delta_{\max}$.
1) *Initialize voting direction and magnitude:* Compute $\nabla(I)$, its magnitude $||\nabla(I)||$, and let the voting direction for each grid point at $S := \{(x, y) | \; ||\nabla(I)|| > \Gamma_g\}$ be

$$\alpha(x, y) := \frac{(I_x(x, y), I_y(x, y))}{||\nabla(I)||}$$

3) *Compute the votes:* $V(x, y; r_{\min}, r_{\max}, \Delta) = 0$. For all pixels $(x, y) \in S$ and $(u, v) \in A(x, y; r_{\min}, r_{\max}, \Delta)$, update the spatial cluster:

$$V(u, v; r_{\min}, r_{\max}, \Delta) = V(u, v; r_{\min}, r_{\max}, \Delta) + ||\nabla(I)||$$

4) *Update the voting direction:* For grid points $(x, y) \in S$, revise the voting direction:

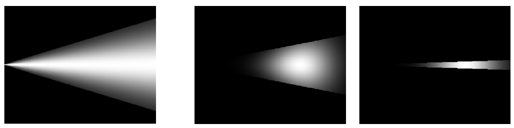
$$(u^*, v^*) = \arg \min_{(u,v) \in A(x,y;r_{\min},r_{\max},\Delta)} V(u, v; r_{\min}, r_{\max}, \Delta)$$

Let $d_x = u^* - x, d_y = v^* - y$, and

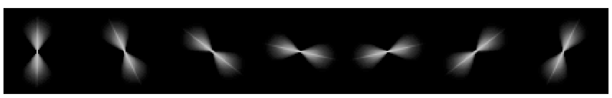
$$\alpha(x, y) = \frac{(d_x, d_y)}{\sqrt{d_x^2 + d_y^2}}$$

5) *Refine the angular range:* Let $n := n - 1$, repeat steps 3-5.
6) *Localize centers of mass:* Localize centers of mass by thresholding

$$\{(x, y)|V(x, y; r_{\min}, r_{\max}, \Delta) > \Gamma_v\}$$

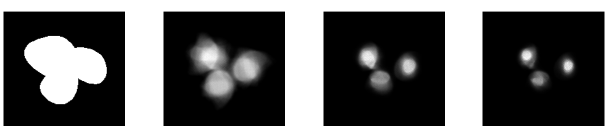


(a) (b) (c)

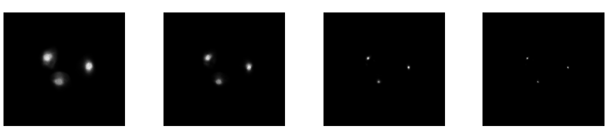


(d)

Figure 2: Kernel topograhy: (a-c) three samples of evolving kernels for detection of radial symmetries; and (d) oriented kernels for voting along tangential directions (shown only at a fixed scale).



(a) (b) (c) (d)



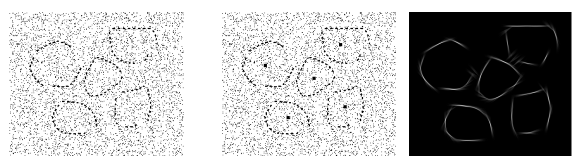
(e) (f) (g) (h)

Figure 3: Search for radial symmetries for synthetic multiple overlapping objects: (a) original image; (b)-(h) voting landscape at each iteration.

Figure 2 shows a subset of voting kernels that vary in topography, scale, and orientation. An example of the application of radial kernels to overlapping objects is shown in Figure 3 together with the intermediate results. The voting landscape corresponds to the spatial clustering that is initially diffused and subsequently refined and focused into distinct islands.

4 Experimental results

The proposed method for detecting of saliency has been applied to a wide class of objects across various application domains. We will show that our method is tolerant to variations in scale, has excellent noise immunity, and can detect overlapping objects with impartial boundaries.
1) *Synthetic data:* Figure 4 shows computed localization of blobs of interest from synthetic images corrupted by noise. In Figure 4(a), boundary information is incomplete, and the problem is one of perceptual grouping. The method is applied along the radial direction to detect centers of mass, and along the trangential direction to infer continuity.
2) *Scientific applications:* Several examples of scientific images are provided to demonstrate extensibility of the method. The first group, shown in Figure 5, are acquired from wide-field and transmission electron microscopy, respectively. These images indicates that (1) blobs of interest have variable scale, (2) these blobs often overlap, and (3) a significant amount of noise is often present, especially for imaging macromolecular assemblies. Figure 6 shows a detailed example corresponding to the evolution of radial symmetries from a tissue section imaged with a confocal microscope. The next example, shown in Figure 7, corresponds to the detection of nuclei in *C. elegans*. Finally, Figure 8 shows detection and refinement of an atmospheric vortex. The intermediate results indicate how the cluster is localized along the radial direction.



(a) (b) (c)

Figure 4: Synthetic images perturbed with noise: (a) objects with incomplete boundaries; (b) detected centroids; and (c) inferred contours.

5 Conclusion and future work

We have proposed an approach for detecting saliency in spatial data. Two new techniques are introduced: re-estimation of voting direction and update of voting fields from coarse to fine. We suggest that the dynamic and evolutionary voting strategy overcomes the drawbacks of traditional static voting. The performance of the method has been demonstrated on synthetic and real data. The method assumes an approximate prior knowledge of scale; however, this is a valid assumption for some applications (e.g., particle picking, nuclei localization). At the same time, the technique merely hypothesizes/infers potential saliency at

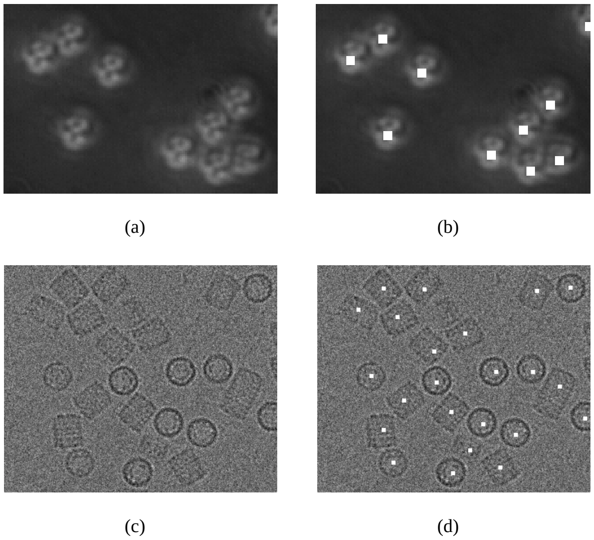


Figure 5: Scientific images: (a,b) cells infected with the SARs virus observed with a wide-field microscope, and (c,d) macromolecular assemblies observed with a transmission electron microscope.

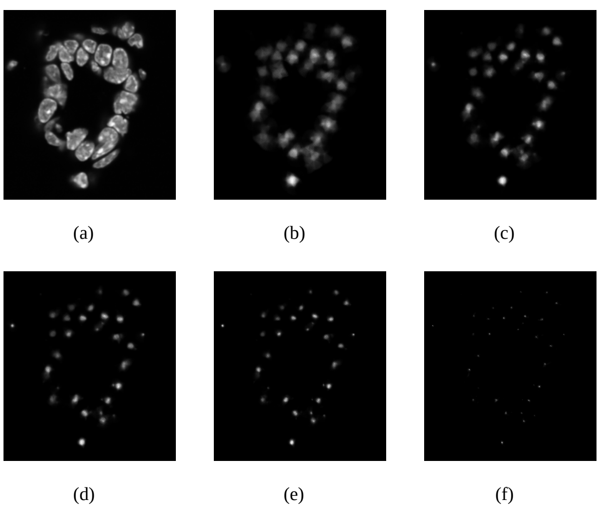


Figure 6: Evolution of the voting landscape for localization of nuclei in a tissue section: (a) the original image; (b)-(f) refinement of the voting map.

a given scale. These inferences need to be verified or validated by other means, which could be yet another higher-level process.

References

[1] F. Attneave. Symmetry information and memory for patterns. *American Journal of Psychology*, 68:209–222, 1955.

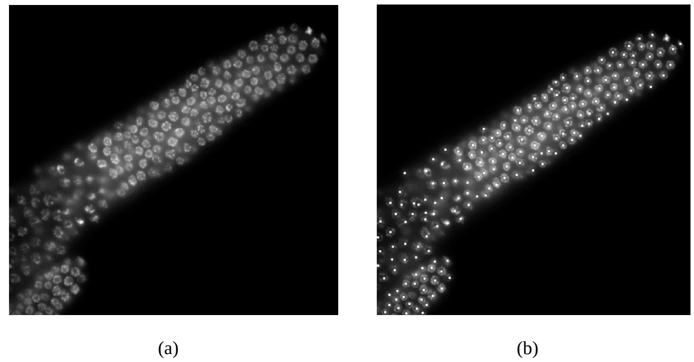


Figure 7: Detected nuclei in *C. elegans* observed through fluorescence microscopy.

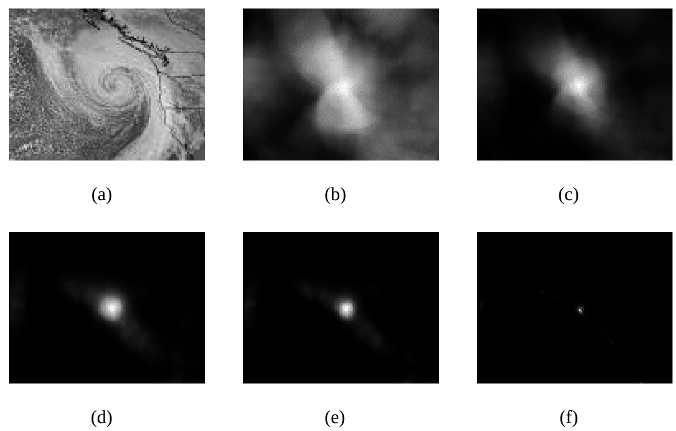


Figure 8: Localization of an atmospheric vortex: (a) original image; (b-f) evolution of the voting landscape.

[2] G. Loy and A. Zelinsky. Fast radial symmetry for detecting points of interest. *PAMI*, 25(8):959–973, August 2003.

[3] G. Medioni, M.S. Lee, and C.K. Tang. *A Computational Framework for Segmentation and Grouping*. Elsevier, 2000.

[4] L.G. Minor and J. Sklansky. The detection and segmentation of blobs in infrared images. *SMC*, 11:194–201, 1981.

[5] D. Reisfeld, H. Wolfson, and Y. Yeshurun. Context-free attentional operators: The generalized symmetry transform. *IJCV*, 14(2):119–130, March 1995.

[6] D. Reisfeld and Y. Yeshurun. Preprocessing of face images: Detection of features and pose normalization. *CVIU*, 71(3):413–430, September 1998.

[7] G. Sela and M.D. Levine. Real-time attention for robotic vision. *Real-Time Imaging*, 3(3):173–194, June 1997.

[8] L. Vincent and P. Soille. Watersheds in digital spaces: An efficient algorithm based on immersion simulations. *PAMI*, 13(6):583–598, June 1991.

[9] Q. Yang and B. Parvin. Harmonic cut and regularized centroid transform for localization of subceullar structures. *IEEE Transactions on Biomedical Engineeing*, 50(4):469–475, April 2003.