Snake Validation: A PCA-Based Outlier Detection Method

Article *in* IEEE Signal Processing Letters · July 2009

DOI: 10.1109/LSP.2009.2017477 · Source: IEEE Xplore

3 authors, including:

Baidya Nath Saha
Concordia University of Edmonton

Hong Zhang
University of Alberta

Snake Validation: A PCA-Based Outlier Detection Method

Baidya Nath Saha, Nilanjan Ray, and Hong Zhang

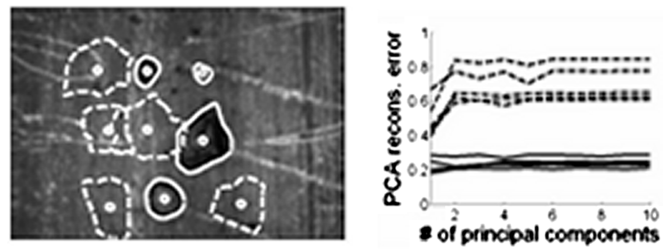
***Abstract*—We utilize outlier detection by principal component analysis (PCA) as an effective step to automate snakes/active contours for object detection. The principle of our approach is straightforward: we allow snakes to evolve on a given image and classify them into desired object and non-object classes. To perform the classification, an annular image band around a snake is formed. The annular band is considered as a pattern image for PCA. Extensive experiments have been carried out on oil-sand and leukocyte images and the performance of the proposed method has been compared with two other automatic initialization and two gradient-based outlier detection techniques. Results show that the proposed algorithm improves the performance of automatic initialization techniques and validates snakes more accurately than other outlier detection methods, even when considerable object localization error is present.**

***Index Terms*—Active contour, classification, principal component analysis, snake.**

I. Introduction

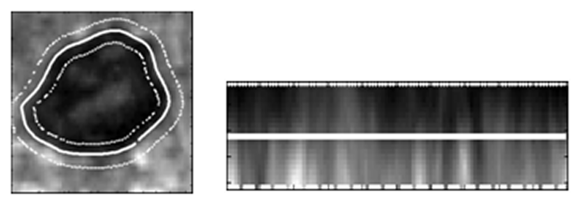
RESEARCH on snake or active contour [6]-based techniques has made them a mature interactive image segmentation tool. However, the techniques are yet to become fully *automated* in many applications. For complete automation, one needs the following three sequential steps: 1) snake initialization; 2) snake evolution; and 3) validation of the evolved snakes. Literature survey shows that much of the effort to date has been exerted on the first two steps, while the last step is practically ignored and left for the application to decide. The automated initialization techniques proposed to date mostly attempt to exploit the structure/shape of the objects (e.g., see [2] and [8]). In this paper we argue that a very crucial step for overall full automation of the snake is necessarily the validation step—often more important than the initialization step—when simple blind/random initializations are possible.

The principle of the proposed snake validation is simple. We place seed points uniformly over the whole image (when no sophisticated initialization is used) and evolve a snake from each seed point [Fig. 1(a)]. When all the snakes converge to their local minima, we construct a pattern image (an annular band around the snake) for each snake (Fig. 2). Next, we project each pattern image into an already trained PC (principal component) space and compute reconstruction error. The snakes associated with lower reconstruction errors than a threshold are identified as objects and others are identified as nonobjects [Fig. 1(b)]. The threshold for PCA reconstruction error is determined by cross validation (leave-one-out) applied on the training set.



(a) (b)

Fig. 1. (a) Seed points (small circle) and evolved snakes. (b) PCA reconstruction errors of these snakes.



(a) (b)

Fig. 2. (a) Annular ring (from innermost to outermost curve) across the contour (middle curve) of the object. (b) Rectangular pattern image.

To experimentally illustrate our snake validation technique, we choose oil sand [7] and leukocyte image [1] segmentations. We have carried out experiments with two automatic initialization techniques ([2] and [8]) and simple blind seed initialization. Results show that these automatic initialization techniques produce many undesired seed points. The snakes evolved from them converge to clutter and our PCA-based outlier detection technique is called upon to improve the performance of the automated segmentation system.

Our experiments also indicate that the proposed validation achieves not only high classification performances, but also robustness to object localization errors when compared with edge strength-based measures.

Although the application of the proposed PCA-based technique for snake validation is novel, it is worth mentioning that PCA has been used successfully in the past for object detection from images [4]. It is noted that a part of the work reported in this communication has appeared in the conference paper [7].

Manuscript received December 09, 2008; revised January 25, 2009. Current version published May 01, 2009. This work was supported by NSERC, iCORE, Syncrude, Matrikon, and the University of Alberta. The associate editor coordinating the review of this manuscript and approving it for publication was Dr. Nikolaos V. Boulgouris.

The authors are with the University of Alberta, Edmonton, AB T6G 2E8 Canada (e-mail: baidya@cs.ualberta.ca; nray1@cs.ualberta.ca; zhang@cs.ualberta.ca).

Digital Object Identifier 10.1109/LSP.2009.2017477

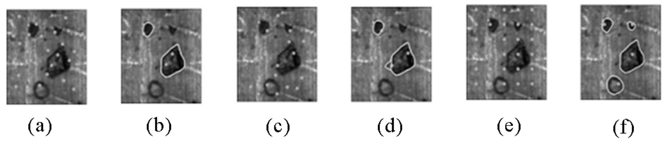


Fig. 3. (a) CoD; (b) CoD with PCA; (c) CP; (d) CP with PCA; (e) blind initialization (uniform spacing between two consecutive seed points); and (f) BI with PCA.

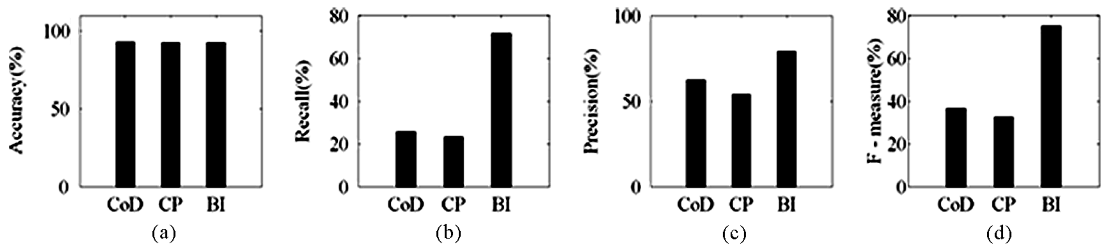


Fig. 4. (a) Accuracy; (b) recall; (c) precision; and (d) F-measure for CoD, CP, and BI.

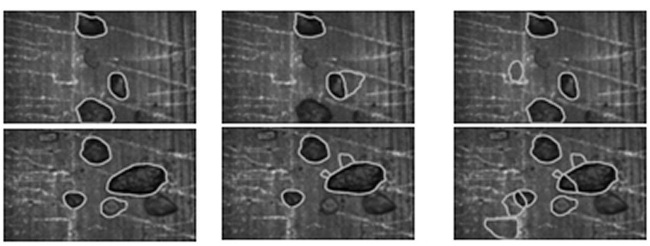


Fig. 5. Oil sand images. Left column: results of our proposed algorithm. Middle column: results of GICOV. Right column: results of average gradient.

II. Outlier Detection by PCA

Given a set of training pattern images, the PCA framework is as follows. Each pattern image I_i of size m-by-n is reshaped into a vector $\mathbf{x}_i$, of size M-by-1, with $M = mn$. Next, p pattern images are combined into a matrix: $[\mathbf{x}_1\mathbf{x}_2 \ldots \mathbf{x}_p]$ of size M-by-p. Then this matrix is centered: $X = [\mathbf{x}_1 - \bar{\mathbf{x}}\mathbf{x}_2 - \bar{\mathbf{x}} \ldots \mathbf{x}_p - \bar{\mathbf{x}}]$, where $\bar{\mathbf{x}} = (1/p)\sum \mathbf{x}_i$. Here typically, $M \gg p$. Using singular value decomposition we have: $X_{M\times p} = U_{M\times p}\, D_{p\times p}(V_{p\times p})^T$, where U's columns are eigenvectors of XX^T, and V's columns are eigenvectors of X^TX, while D is a diagonal matrix with the diagonal elements d_i, the singular values, which are the square roots of the eigenvalues λ_i of XX^T (or X^TX) and are usually ordered so that $\lambda_i \geq \lambda_{i+1}, i = 1, 2, \ldots, p-1$. After PCA on the pattern images, we can project a new or test pattern image $\mathbf{x}$ into the PC-subspace composed of only $d \ll M$ eigenvectors (first d columns of $U_{M\times p}$): $\tilde{\mathbf{x}} = \bar{\mathbf{x}} + U_{M\times d}(U_{M\times d})^T(\mathbf{x} - \bar{\mathbf{x}})$. PCA reconstruction error for the test image $\mathbf{x}$ is defined as: $||\mathbf{x} - \tilde{\mathbf{x}}||^2$, where $||\cdot||$ denotes the Euclidean norm. If the test pattern image $\mathbf{x}$ belongs to the same class as the training images, then this reconstruction error will be small; otherwise, it will be large [3].

III. Pattern Image Formation

Fig. 2(a) shows a snake (in solid line) and an annular ring denoted by dotted contours. The pattern image is formed by unfolding the annular ring into a rectangular image [Fig. 2(b)]. These pattern images carry object texture information near the object boundary that has good discrimination capability as our experiments show. The width of the pattern image is chosen based on the object size and image intensity profile near the object boundary.

IV. Results and Discussions

We have carried out experiments on two types of data sets: oil sand images and leukocyte microscopy images.

A. Experiments on Oil Sand Images

Oil sand images are captured by a mounted video camera looking down at conveyor belt. Oil sand mining can benefit from the computation of oil sand particle size distribution (PSD) at various stages of mining operations. To determine PSD oil sand particles are segmented from the conveyor belt images and their areas are computed. For further details, see [7].

We have constructed training set using five images and test set using 100 images sampled randomly from an online video of oil sand particles over conveyor belt.

1) Computation on Training Set: We form ten rectangular pattern images by unfolding an annular ring of 5 pixels' width both inside and outside across the contour of ten oil sand particles and use them in PCA computation. Experiments show that only the first principal component linked to the maximum Eigen value explains the maximum percentage of variance (80% of the total variance). We use the leave-one-out cross validation to compute the threshold for PCA reconstruction error.

2) Experiments on Test Set: We evolve 30 snakes keeping at uniform distance on each of the 100 test images. We utilize a modified version of GVF (gradient vector flow) snake here. The advantage of using such a snake is its insensitivity to seed initialization and was reported in [7]. When all snakes have converged to their local minima, we form a pattern image for each snake and project it into the PCA space and compute reprojection error based on only the first principal component. We have compared our PCA-based outlier detection with two automatic initialization techniques: center of divergence [2] and critical point [8]

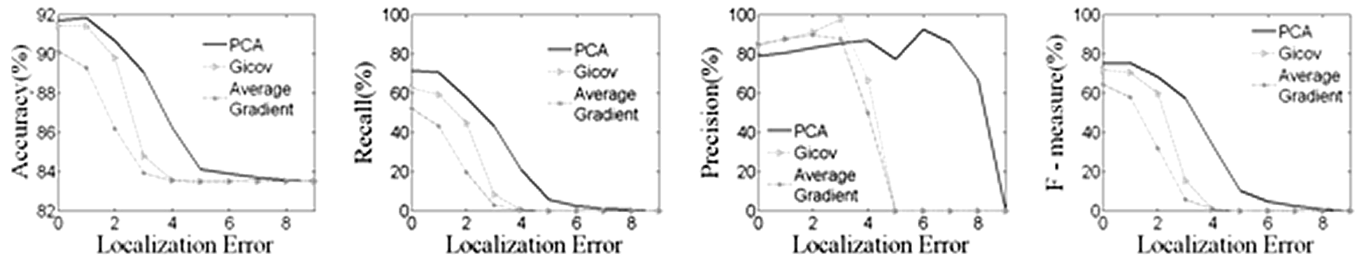


Fig. 6. Accuracy, recall, precision, and F- measure versus localization error for oil sand images.

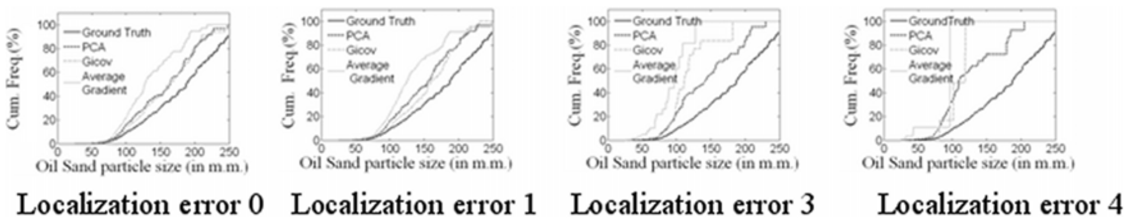


Fig. 7. PSD versus localization error for oil sand images.

and two gradient-based techniques: GICOV [1] and average directional image gradient computed on evolved snake contours.

3) Experiments on CoD and CP: Center of divergence (CoD) [2] corresponds to the local maxima of the external energy field. CoD is defined as the point from which the GVF vectors of all the neighboring pixels radiate. Wang *et al.* [8] suggested the idea of critical point (CP) [8], which is defined as the point from which the quantized GVF vectors of its 8-neighborhood do not point to it. Both of these methods tend to initialize more than the desired number of active contours, i.e., the image is over segmented. Visual results of COD, CP, and blind initialization (BI) techniques are shown in Fig. 3. CoD and CP yield 31 seed points on an average on each image and whereas we evolve 30 snakes keeping at uniform distance on each image in BI. We measure accuracy, recall, precision and F-measure [5] for COD, CP and BI techniques with proposed PCA validation technique shown in Fig. 4. F-measure combines recall and precision into a single entity with a higher value indicating better performance. Results show that BI with PCA validation technique recalls at least 45% better, detects at least 20% more precisely than CoD and CP. The F-measure for BI with proposed PCA technique is also larger than those for CoD and CP.

4) Experiments on Gradient-Based Techniques: GICOV is the ratio of average directional image derivative and their standard deviation. GICOV and average gradient both require a threshold value to decide whether a contour is the desired object or not. We compute these threshold on the same training set used for PCA. Detections obtained by the proposed PCA, GICOV and average directional derivative techniques are shown in Fig. 5, which illustrates that the proposed algorithm is superior to its competitor for these images.

To assess robustness, we have randomly shifted each converged snake contour up to 9 pixels along horizontal/vertical direction and measured performance of these three techniques. The total amount of shift of a snake contour from its local minima is referred to as localization error. We measure accuracy, recall, precision and F-measure [5] for different localization errors shown in Fig. 6. Fig. 6 shows that our PCA-based snake confirmation test is up to 10% more accurate, recall up to 20% better and it can sustain more localization error (at least 5–6 pixels). The F-measure value for proposed PCA technique is always larger than those of GICOV and average gradient. The robustness of the proposed PCA-based method can be attributed to the proposed annular pattern images that capture image texture information near the object boundaries.

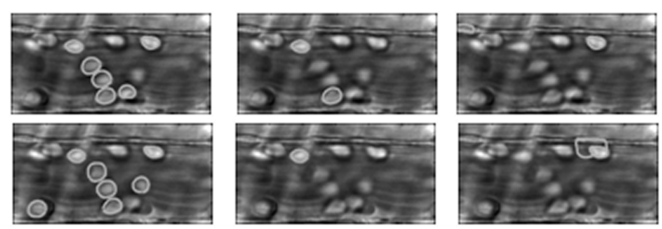


Fig. 8. Leukocyte images. Left column: results proposed algorithm. Middle column: results of GICOV. Right column: results of average gradient.

Fig. 7 shows PSD at different localization errors and it shows again that PCA can sustain more localization error as PCA PSD curve deviates less from expert labeled ground-truth PSD than GICOV and average gradient methods.

B. Experiments on Leukocyte Images

Identifying and counting rolling leukocytes from intravital video microscopy are imperative in the study of inflammation as well as in the design of anti/pro-inflammatory drugs [1]. We have used a training set of five images and a test set of 25 images here and carried out the experiments similar to those reported in Section IV-A. Detections obtained by the proposed PCA, GICOV, and average directional derivative techniques are shown in Fig. 8, and their comparison in terms of accuracy, recall, precision and F-measure for different localization errors (in pixels) is shown in Fig. 9. One can conclude that the proposed algorithm is up to 5% more accurate, and its recall is up to 30% better than the competing methods. In addition, our proposed

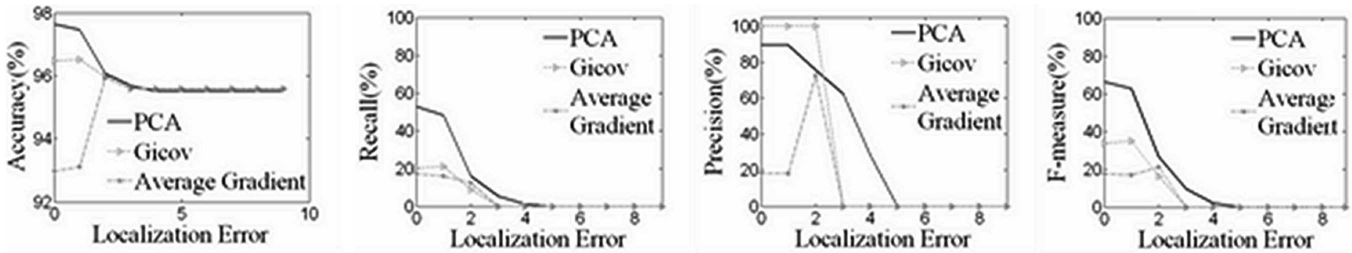


Fig. 9. Accuracy, recall, precision and F-measure versus localization error for leukocyte image.

method can handle significant localization errors of as much as 5 or 6 pixels.

V. Conclusion and Future Work

We propose a PCA-based snake validation method that is a crucial part of a fully automated snake segmentation technique. Our method can be used as a plug-in with a snake evolution technique to certify the evolved snake as a desired object or clutter when there does exist a bright to dark transition across the contour. Because the proposed method is based on a pattern image made around the evolved snake, it is robust to object localization error. Also, when simple seed-like snake initialization strategies work for an application, we often suffice to have blind lattice-like seed points along with the proposed validation method. When many such seeds could be a waste in computation, judicious initialization may cut back the time. However, our experiments suggest that even with smart snake initialization techniques, a validation step should not be skipped.

References

[1] G. Dong, N. Ray, and S. T. Acton, "Intravital leukocyte detection using the gradient inverse coefficient of variation," *IEEE Trans. Med. Imag.*, vol. 24, no. 7, pp. 910–924, Jul. 2005.

[2] X. Ge and J. Tian, "An automatic active contour model for multiple objects," in *Proc. ICPR*, 2002, pp. 881–884.

[3] I. T. Jolliffe, *Principal Component Analysis*, 2nd ed. New York: Springer, 2002.

[4] L. Malagon-Borja and O. Fuentes, "An obj. detection system using image reconstruction with PCA," in *Proc. 2nd Canadian Conf. Comp. Robot Vis.*, 2005, pp. 2–8.

[5] C. J. van Rijsbergen, *Information Retrieval*. London, U.K.: Butterworths, 1979.

[6] M. Kass, A. Witkins, and Terzopoulos, "Snakes: Active contour models," in *Int. J. Comput. Vis.*, 1987, pp. 321–331.

[7] B. N. Saha, N. Ray, and H. Zhang, "Computing oil sand particle size distribution by snake-PCA algorithm," in *Proc. ICASSP*, Las Vegas, NV, Nov. 2008.

[8] Y. Q. Wang, J. Liang, and Y. D. Jia, "On the critical point of GVF snake," in *Proc. ACCV*, 2007, pp. 754–763.