Multichannel Texture Image Segmentation using Local Feature Fitting based Variational Active Contours

V. B. Surya Prasath*
Dept. of Computer Science
University of Missouri
Columbia, MO, USA
prasaths@missouri.edu

K. Palaniappan
Dept. of Computer Science
University of Missouri
Columbia, MO, USA
palaniappank@missouri.edu

Guna Seetharaman
Air Force Research Laboratory
Rome, NY, USA
Gunasekaran.Seetharaman@rl.af.mil

ABSTRACT

We study an efficient texture image segmentation model for multichannel images using a local feature fitting based active contours scheme. Using a chromaticity-brightness decomposition, we propose a flexible segmentation approach using multi-channel texture and intensity in a globally convex continuous optimization framework. We make use of local feature histogram based weights with the smoothed gradients from the brightness channel and localized fitting for the chromaticity channels. A fast numerical implementation is described using an efficient dual minimization formulation and experimental results on synthetic and real color images indicate the superior performance of the proposed method compared to related approaches. The novel contributions include the use of local feature density functions in the context of a luminance-chromaticity decomposition combined with a globally convex active contour variational method to capture texture variations for image segmentation.

Keywords

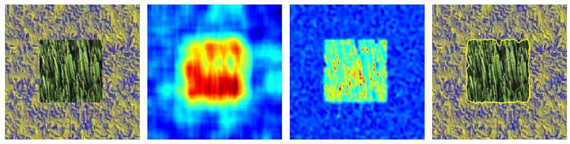
Active contours, Color, Texture Segmentation, Local Histogram, Feature fitting.

1. INTRODUCTION

Color texture image segmentation is still an active area of research in computer vision. In this paper we consider the segmentation of images composed of natural textured regions using active contour methods in a globally convex formulation. One of the key contributions of the paper is combining local feature histograms with a luminance-chromaticity decomposition to adaptively model texture changes in the scene. Starting with the pioneering work of Mumford and Shah [22], variational techniques for image segmentation have become very popular due to their strong mathematical representation and the availability of a variety of numerical techniques for solving such problems. Active contour based solutions for such variational techniques are widely used in image segmentation [20], and one of the important contribution is by Chan and Vese [9, 33] who studied the problem using the level set method [25]. However, such contour based schemes are mainly guided by boundary smoothness along with global regional properties such as mean and variance and hence cannot segment natural scenes with multiple textured regions very well. Thus, it is necessary to introduce extra feature fitting terms to the usual segmentation algorithm [10].

*Corresponding author.

ICVGIP '12, December 16-19, 2012, Mumbai, India



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

Figure 1: Using different feature fitting channels, the proposed scheme segments the textured foreground region accurately. (a) Input color image (b) Weighted gradient of the brightness channel (c) Sum of localized chromaticity channels (d) Segmentation output using the proposed scheme which combines luminance edges with chrominance local distributions.

Different approaches exist that deal with the problem of extracting texture features for using active contour based approaches, and we mention a few of these. Sandberg et al [31] propose Gabor filter based feature fitting channels model, Luis-Garcia et al [19] consider a local structure tensor based approach, see also [34] for a related work using extended structure tensor. Further, to capture non-homogeneous textured segments, region scalable image fitting (RSF) terms play an important role [18, 17]. Modifying the traditional Chan and Vese type scheme by utilizing various feature fitting for specific tasks has been considered by some recent works [29, 32, 30, 1, 11, 12].

In this paper, we propose an extension of the traditional multichannel Chan and Vese model [9] to segment color images composed of textured regions. Utilizing the chromaticity-brightness (CB) model [16] we first decompose the given image and then use two different feature fitting terms to drive the level set based active contour segmentation. Note that the underlying geometric structure of a color image is present in the brightness (intensity) channel alone [6]. We utilize a hybrid feature fitting using the smoothed gradient image computed from the brightness channel, to capture strong intensity variations in the neighborhood of edges, combined with local histogram based weights. That is, the smoothed gradient image of the brightness channel is weighted by the local histograms computed around each pixel of the intensity channel alone. This provides an adaptive force for the active contour to wrap around strong discontinuities. Following the success of region scalable fitting energy terms [18] in capturing spatially varying regions, we utilize local features in the remaining chromaticity channels to capture smoothly varying color fields. Further, our method is based on the globally convex formulation of Chan et al [8] and is implemented using the efficient dual minimization approach of Chambolle [7]. The proposed model is tested on a variety of natural texture images.

The rest of this paper is organized as follows. Section 2 describes the proposed weighted feature fitting active contour model and presents some extensions combined with traditional image fitting based models. Outline of the dual minimization based scheme for implementation is also given. In Section 3, we present experimental and comparison results. Finally, Section 4 concludes the paper.

2. LOCAL FEATURE FITTING BASED ACTIVE CONTOUR

Let Ω be an open and bounded set in $\mathbb{R}^2$, and $\mathbf{I} : \Omega \to \mathbb{R}^N$ be the input multichannel image. In what follows, we study the traditional color images $N = 3$, $\mathbf{I} = (I^1, I^2, I^3)$ where the three spectral channels can be (Red, Green, Blue) bands or other color coordinates such as YUV or HSV and the general multichannel case follows in a straightforward way.

2.1 Globally convex model

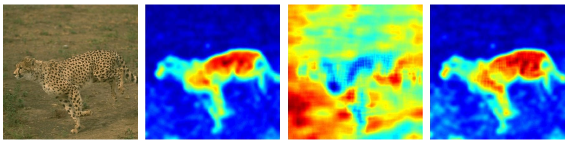
The convex formulation of the traditional vector valued Chan and Vese model [9], amounts to solving the minimization problem [8]:

$$\min_{0\le u\le 1} \left\{ \mu \int_\Omega |\nabla u| \, dx + \sum_{i=1}^{3} \int_\Omega \lambda_i \, R^i(x, c^i) \, u \, dx, \right\} \qquad (1)$$

where $u : \Omega \to [0, 1]$ is a function of bounded variation, $u \in BV(\Omega)$ and $R^i(x, \mathbf{c}^i) = (I^i - c^i_{in})^2 - (I^i - c^i_{out})^2$ which is known as the image fitting term. The vector $\mathbf{c}^i = (c^i_{in}, c^i_{out})$ represents the averages (mean values) of each channel I^i, respectively inside and outside of the segmentation contour. The parameters λ_i are positive scalars weighting the fitting terms $R^i(x, c^i)$. The total variation term (first term in Eqn.(1)) keeps the segmentation curve regular. It can be shown that for any $\lambda_i \ge 0$, there exists a minimizer u of (1), which is a global minimum [8]. The energy functional is homogeneous of degree one in u and has a global minimizer by restricting u such that $0 \le u(x) \le 1$.

Since the Chan and Vese model relies on mean gray values of the input channel I^i alone (for each channel i), it can neither capture the spatially varying intensity regions nor textured regions. In this paper we extend the globally convex Chan-Vese model (1) to support more general fitting terms and to handle textured regions across multiple channels.

2.2 Decomposition - based fitting terms



(a) $\mathbf{I}$ (b) $|\nabla B|_\sigma$ (c) ω (d) $\tilde{B}$

Figure 2: Combining local histogram-based weights with the smoothed luminance gradient field provides a strong feature for texture segmentation. (a) Input color image (b) Smoothed gradient image $\sigma = 10$ (c) Weight map computed from local histograms, see Eqn. (3) (d) Final locally adapted feature channel, Eqn (4).

First we use the chromaticity-brightness (CB) decomposition which provides the intensity or brightness $B : \Omega \to [0, L]$ computed as $B = |\mathbf{I}|$, where L is the maximum intensity value, and the chromaticity channels $\mathbf{C} = (C^1, C^2, C^3) : \Omega \to \mathbb{S}^2$ where $\mathbb{S}^2$ is the unit sphere in $\mathbb{R}^3$.

Intensity and edge-based feature fitting.
Image discontinuities such as edges are of major geometrical structures and are primarily present in the brightness channel alone. We introduce a brightness-based edge feature fitting term using local histograms and the smoothed gradient image to capture objects differentiated by strong discontinuities, see Figure 1(b). For a given gray-scale image $B : \Omega \to [0, L]$, let $\mathcal{N}_{x,r}$ be the local region centered at x with radius r. Then the local histogram of a pixel $x \in \Omega$ and its corresponding cumulative distribution function are defined by

$$P_x(y) = \frac{|\{z \in \mathcal{N}_{x,r} \cap \Omega \,|\, B(z) = y\}|}{\mathcal{N}_{x,r} \cap \Omega}$$
$$F_x(y) = \frac{|\{z \in \mathcal{N}_{x,r} \cap \Omega \,|\, B(z) \le y\}|}{\mathcal{N}_{x,r} \cap \Omega} \qquad (2)$$

for $0 \le y \le L$, respectively. Local histograms provide a general local first-order statistical model of the image intensity values around a pixel without making simplifying assumptions. We define the following measurable function $\omega : \Omega \to \mathbb{R}$, such that for each $x \in \Omega$

$$\omega(x) = \int_0^L F_x(y) \, dy, \qquad (3)$$

which allows us to get a weight of how much non-homogeneous intensity is present in a local region $\mathcal{N}_{x,r}$ of a given pixel $x \in \Omega$. Given an image with texture information, it is possible to extract major regional textures using a weighted and smoothed gradient image, see Figure 2. Then, a new input feature channel is defined by the product

$$\tilde{B} = \omega \times |\nabla B|_\sigma \qquad (4)$$

where the lower sub-script σ in (4) means a smoothed version of the corresponding indexed function. The smoothing is done by a Gaussian kernel $G_\sigma(x) = (2\pi\sigma)^{-1} e^{-\frac{|x|^2}{2\sigma}}$. The new weighted input channel uses the smoothed gradient to differentiate the object boundaries with the help of local histograms computed within each pixel neighborhood that assists in distinguishing edges between textured foreground and the background. Thus the modified brightness fitting term we use is

$$F_B(x,\mathbf{c}) = (\tilde{B} - c_{in})^2 - (\tilde{B} - c_{out})^2. \tag{5}$$

Chromaticity based localized fitting.

As can be seen in Figure 4(b) the chromaticity channels exhibit in-homogeneous and spatially varying nature. Following [18], we utilize a sum of region scalable fitting terms

$$F_C(x,\mathbf{c}) = \sum_{i=1}^{3}\Big[\Big|G_\sigma \star C^i - c_{in}^i\Big|^2 - \Big|G_\sigma \star C^i - c_{out}^i\Big|^2\Big] \tag{6}$$

to capture chromatic regions in across the scene efficiently.

2.3 Combined local feature fitting model and extensions

We combine the different local feature measurements into a single energy functional composed of the weighted luminance edge information with the chromaticity-based region information. Thus, the active contour based scheme we propose can be written as a variational energy minimization problem with a total variation regularization component,

$$\min_{0\le u\le 1,c} \mathcal{E}(u,c) = \mu\int_\Omega |\nabla u| + \int_\Omega (\lambda_B\, F_B + \lambda_C\, F_C)\, u\, dx \tag{7}$$

where $\lambda_B \geq 0$, $\lambda_C \geq 0$ are the tunable parameters for the brightness and total chromaticity feature fitting terms respectively.

Further, the following extensions can be considered

- Balanced form of the model:

  $$\min_{0\le u\le 1,c} \mathcal{E}(u,c) = \mu\int_\Omega |\nabla u| + \beta\int_\Omega (\lambda_B\, F_B + \lambda_C\, F_C)\, u\, dx + (1-\beta)\int_\Omega R\, u\, dx \tag{8}$$

  where $R = \sum_{i=1}^3 (I^i - c_{in}^i)^2 - (I^i - c_{out}^i)^2$ is the usual Chan and Vese global image fitting terms for the color channels and $\beta \in [0,1]$.

- For multichannel images (with $N > 3$) a similar CB decomposition strategy can be used to get texture segmentations. That is, we can compute 'chromaticity' images C^i by dividing out the intensity image B for each channel $i = 1,\ldots N$. The final segmentation model is given by

  $$\min_{0\le u\le 1,c} \mathcal{E}(u,c) = \mu\int_\Omega |\nabla u| + \int_\Omega (\lambda_B\, F_B + \lambda_C\, F_C)\, u\, dx$$

  with F_B as in Eqn. (5) and F_C is given by Eqn. (6) where the sum is now taken across all N channels.

In addition to brightness and chromaticity fitting terms other image features can be used such as local multichannel edges [5, 4] , local shape [26, 15, 3], local texture [14], or local motion [27, 21, 28] in a variety of computer vision and biomedical segmentation and tracking applications.

2.4 *Fast Dual Minimization implementation*

A fast numerical scheme based on Chambolle's dual minimization technique [7] for total variation regularization is implemented for solving the proposed minimization problem (7). We briefly sketch the major steps as follows. Following, Chan et al [8] we first consider the corresponding unconstrained convex minimization functional (with $\mu = 1$):

$$\min_{u,v}\left\{\int_\Omega |\nabla u|\, dx + \frac{1}{2\theta}\|u-v\|^2_{L^2(\Omega)} + \int_\Omega (\lambda_B\, F_B + \lambda_C\, F_C)\, v + \alpha\nu(v) dx\right\}, \tag{9}$$

where θ is chosen to be small, $\nu(\xi) := \max\{0, 2|\xi - \frac{1}{2}| - 1\}$ and $\alpha > \frac{\max{(\lambda_B,\lambda_C)}}{2}\|r\|_{L^\infty(\Omega)}$. Then (9) is split into the following two alternating minimization problems:

1. Minimize for u

   $$\left\{\int_\Omega |\nabla u|\, dx + \frac{1}{2\theta}\|u-v\|^2_{L^2(\Omega)}\right\},$$

   for which the solution is given by: $u = v - \theta div\, p$. The vector $p = (p_1, p_2)$ is given by $\nabla(\theta div\, p - v) - |\nabla(\theta div\, p - v)|p = 0$ and can be solved by a fixed point method: $p^0 = 0$ and

   $$p^{n+1} = \frac{p^n + \delta t \nabla(\theta div(p^n) - v/\theta)}{1 + \delta t|\nabla(\theta div(p^n) - v/\theta)|}.$$

2. Minimize for v

   $$\left\{\frac{1}{2\theta}\|u-v\|^2_{L^2(\Omega)} + \int_\Omega \lambda(\lambda_B\, F_B + \lambda_C\, F_C)v + \alpha\nu(v) dx\right\},$$

   for which the solution is given by:

   $$v = \min\left\{\max\left(u(x) - \theta(\lambda_B\, F_B + \lambda_C\, F_C), 0\right), 1\right\}$$

   .

The constants c_{in} and c_{out} are updated every few iterations (typically every 10 iterations) of the above algorithm. For example, the brightness channel values are updated by

$$c_{in}(u) = \frac{\int_{\Sigma_\mu} u\, dx}{|\Sigma_\mu|} \quad \text{and} \quad c_{out}(u) = \frac{\int_{(\Sigma_\mu)^c} u\, dx}{|(\Sigma_\mu)^c|}, \tag{10}$$

where $\Sigma_\mu = \{x \in \Omega \,:\, u(x) \geq \mu\}$, with μ any arbitrary point in $[0, 1]$. Similar computations for the chromatic channel values $\mathbf{c^i} = (c^i_{in}, c^i_{out})$ are carried out. The above scheme helps in finding the global minimizer of the energy functional, see [2] for more details.

3. EXPERIMENTAL RESULTS

The proposed scheme based on dual minimization algorithm is implemented in MATLAB7 R2012a on a Windows 7 laptop with Intel Core2 Duo processor, with 2.20GHz and all the images are scaled to the interval $[0, 1]$. For a color image of size $321 \times 321 \times 3$, the proposed scheme takes about 20 seconds to get the final segmentation result (80 iterations for the dual minimization method). We expect further speed-up of the scheme with the use of GPU based histogram computation as well as utilizing the more efficient split Bregman technique [13] for the energy minimization. In all the experiments reported here, the parameters were fixed at $\delta t = 1/8$, $\sigma = 10$, $r = 10$, $\lambda = 1$ and $\theta = 1$.

The segmentation results of our scheme Eqn. (7) are compared with the multichannel Gabor filters based Chan-Vese model [31, 9] and also with a state of the art local histogram based scheme from [24]. The total number of iterations for Gabor - Chan and Vese is set at 1000 and the regularization parameter $\mu = 1$, for the Ni et al [24] scheme we used the same parameters as in our case and it matches the results provided in [24]. Note that the Ni et al's scheme [24] works only with gray-scale images. Recently an extension of the scheme to color images is presented in Bao et al [1] which uses the same local histogram feature fitting term under a CB decomposition approach. Thus, Bao et al [1] inherits the same problems of the original formulation. The tunable parameters λ_B, λ_C can be set according to image chromaticity information, for example when there are small scale textures, the chromaticity based localized fitting should be given more weight than the weighted gradient based feature fitting, i.e., $0 \leq \lambda_B < \lambda_C \leq 1$, see Figure 3 for an example.

3.1 Synthetic images

Figure 4 shows the comparison results for a synthetic texture image which consist of two different textured regions. As can be seen the proposed approach's result given in Figure 4(f) provides a better segmentation than the multichannel Gabor - Chan and Vese model [31], Figure 4(c), the Ni et al [24] scheme result, Figure 4(d) as well as the result from Bao et al [1](e). The chromatic feature fitting term Eqn. (6) given in Figure 4(b) shows that using localized fitting results in the central region of the image being accurately identified which provides a better qualitative segmentation result.

3.2 Natural images

Figure 5 shows some segmentation results for natural images taken from Berkeley Segmentation Dataset which contain difficult texture objects. The segmentation results given in Figure 5 shows the advantage of using balanced weighted information based on local histograms with smoothed gradients along with localized chromatic fitting terms. For example, comparing the segmentation results for the *Cheetah* image in Figure 5 (first row), we see that better segmentation is obtained using the proposed approach, whereas the scheme from [24] produced disjointed segments of the *Cheetah*'s body, see for example the tail section. This can be attributed to the fact the scheme in [24] uses only the local histogram based feature channel given in Figure 5(c) and does not use any discontinuity information such as smoothed gradients or localized image fitting channel, see Figure 5(e). The Gabor filters based Chan and Vese [31] on the other hand suffers from spurious segments as can be seen in Figure 5(b). This is due to the fact that the Gabor filters are very sensitive to small scale textures and can easily lose salient object boundaries due to their localization property. Similarly, for the *Eel* image given in Figure 5 (second row) we obtain a single unified segment whereas the scheme from [24] gives spurious segments at the left hand and right bottom side of the image. The final row highlights the importance of chromaticity-based localized fitting terms. Our proposed scheme gives segmentation of the *Snake* whereas the gray-scale feature fitting based schemes fail completely. Note that for this image we set the parameters $\lambda_B = 0.2$, $\lambda_C = 0.8$.

4. CONCLUSION

In this paper, we present a new texture segmentation scheme driven by local feature energy terms, using the globally convex formulation of an extended Chan and Vese active contours without edges model. Our scheme uses local density functions to model texture information in the luminance channel and combines this with smoothed gradient edge information. By utilizing a localized feature fitting for the chromaticity channels we obtain a combined model which helps in segmenting textured regions effectively. Experimental results on synthetic and natural texture images demonstrates the improved performance of the method compared with previous models such as Gabor filter based vector Chan and Vese and local histogram-based approaches. Our current efforts include using extended structure tensor based texture features [23] that are invariant to illumination changes for improving segmentation results as well as using our scheme for multispectral image segmentation.

5. ACKNOWLEDGEMENT

The first author would like to thank the Fields Institute, Toronto, Canada for their great hospitality and support during the Thematic Program on Inverse Problems and Imaging where part of this work was done. He also thanks Dr. Juan C. Moreno (Univ. Coimbra, Portugal) for discussions on local feature fitting terms. Authors thank anonymous reviewers for their comments which improved the paper.

This research was partially supported by U.S. Air Force Research Laboratory (AFRL) and approved for public release. The views and conclusions contained in this document are those of the authors and should not be interpreted as representing the official policies of AFRL or the U.S. Government. The U.S. Government is authorized to reproduce and distribute reprints.

6. REFERENCES

[1] Z. Bao, Y. Liu, Y. Peng, and G. Zhang. Variational color image segmentation via chromaticity-brightness decomposition. In *Advances in Multimedia Modeling*, pages 295–302, 2010. Springer LNCS 5916.

[2] X. Bresson, S. Esedoglu, P. Vandergheynst, J. Thiran, and S. Osher. Fast global minimization of the active contour/snake model. *Journal of Mathematical Imaging and Vision*, 28(2):151–167, 2007.

[3] F. Bunyak, K. Palaniappan, O. Glinskii, V. Glinskii, V. Glinsky, and V. Huxley. Epifluorescence-based quantitative microvasculature remodeling using geodesic level-sets and shape-based evolution. In *30th Int. IEEE Engineering in Medicine and Biology Society Conf. (EMBC)*, pages 3134–3137, Vancouver, Canada, Aug. 2008.

[4] F. Bunyak, K. Palaniappan, S. K. Nath, and G. Seetharaman. Flux tensor constrained geodesic active contours with sensor fusion for persistent object tracking. *J. Multimedia*, 2(4):20–33, August 2007.

[5] F. Bunyak, K. Palaniappan, S. K. Nath, and G. Seetharaman. Geodesic active contour based fusion of visible and infrared video for persistent object tracking. In *8th IEEE Workshop Applications of Computer Vision (WACV 2007)*, page Online, Austin, TX, Feb. 2007.

[6] V. Caselles, B. Coll, and J.-M. Morel. Geometry and color in natural images. *Journal of Mathematical Imaging and Vision*, 16(2):89–105, 2002.

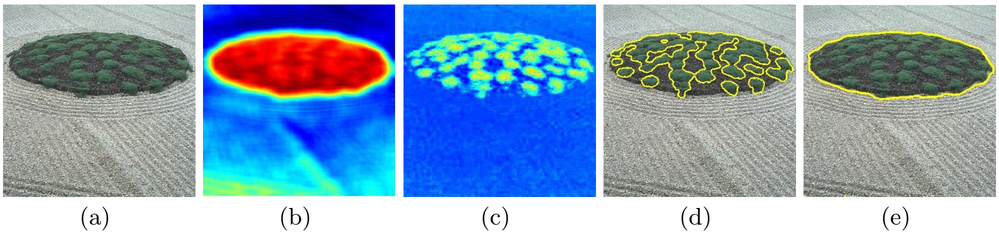


Figure 3: Role of weighting parameters λ_B, λ_C on final segmentation results: (a) Input image consist of a big circle with small scale texture objects with strong chromaticity (b) Brightness based feature fitting term F_B, Eqn. (5) (c) Total chromaticity based localized fitting F_C, Eqn. (6) (d) Segmentation result of our scheme (7) with $\lambda_B = 0$, $\lambda_C = 1$ (e) Segmentation result of our scheme (7) with $\lambda_B = 1$, $\lambda_C = 0$.

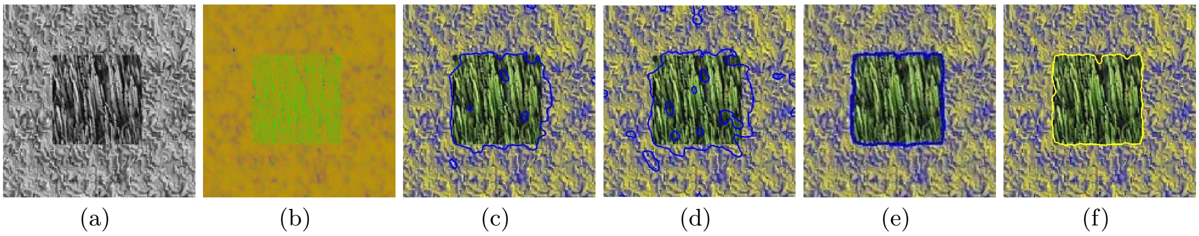


Figure 4: Input feature channels: (a) Brightness channel (B) (b) Total Chromaticity channel ($\sum_{i=1}^{3} C^i$) and Comparison of segmentation results (c) Gabor - Chan and Vese model [31] (d) Ni et al [24] (e) Bao et al [1] (f) Proposed scheme Eqn. (7) with $\lambda_B = 0.2$, $\lambda_C = 0.8$.

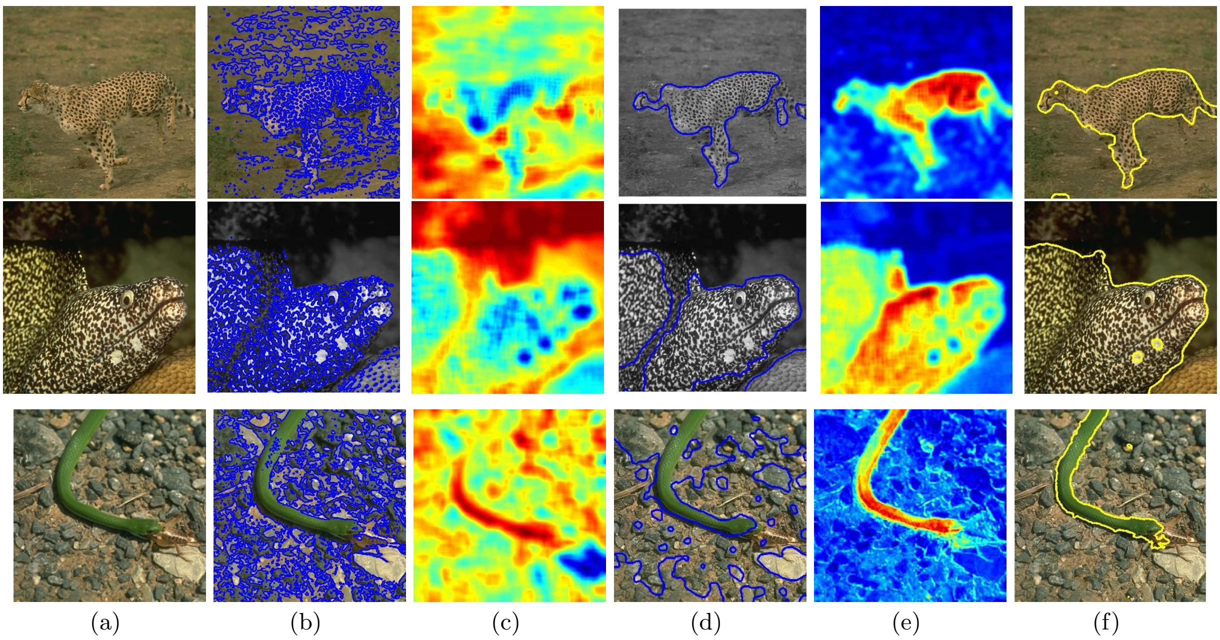


Figure 5: Comparison of segmentation results for different challenging texture images. In each row: (a) Input image (b) Gabor - Chan and Vese model [31] result (c) Local histogram based feature channel (d) Ni et al [24] segmentation result (e) Local feature fitting channel (f) Our segmentation result.

[7] A. Chambolle. An algorithm for total variation minimization and applications. *Journal of Mathematical Imaging and Vision*, 20(1–2):89–97, 2004.

[8] T. F. Chan, S. Esedoglu, and M. Nikolova. Algorithms for finding global minimizers of image segmentation and denoising models. *SIAM Journal on Applied Mathematics*, 66(5):1632–1648, 2006.

[9] T. F. Chan and L. A. Vese. Active contours without edges. *IEEE Transactions on Image Processing*, 10(2):266–277, 2001.

[10] D. Cremers, M. Rousson, and R. Deriche. A review of statistical approaches to level set segmentation: integrating color, texture, motion and shape. *International Journal of Computer Vision*, 72(2):195–215, 2007.

[11] I. N. Figueiredo, J. C. Moreno, and V. B. S. Prasath. Texture image segmentation with smooth gradients and local information. In *Computational Modeling of Objects Presented in Images: Fundamentals, Methods and Applications (CompIMAGE 2012)*, pages 164–171, Rome, Italy, September 2012.

[12] I. N. Figueiredo, J. C. Moreno, V. B. S. Prasath, and P. N. Figueiredo. A segmentation model and application to endoscopic images. In *International Conference on Image Analysis and Recognition (ICIAR 2012)*, pages 164–171, Aveiro, Portugal, June 2012. Springer LNCS Volume 7325 (eds.: A. Campilho and M. Kamel).

[13] T. Goldstein, X. Bresson, and S. Osher. Geometric applications of the split Bregman method: segmentation and surface reconstruction. *Journal of Scientific Computation*, 45(1–3):272–293, 2010.

[14] A. Hafiane, F. Bunyak, and K. Palaniappan. Fuzzy clustering and active contours for histopathology image segmentation and nuclei detection. In *Advanced Concepts for Intelligent Vision Systems (ACIVS)*, pages 903–914, Juan-les-Pins, France, October 2008. Lecture Notes in Computer Science, Volume 5259.

[15] I.Ersoy, F.Bunyak, M.A.Mackey, and K.Palaniappan. Cell segmentation using Hessian-based detection and contour evolution with directional derivatives. In *IEEE Int. Conf. Image Processing*, pages 1804–1807, Oct. 2008.

[16] S. H. Kang and R. March. Variational models for image colorization via chromaticity and brightness decomposition. *IEEE Transactions on Image Processing*, 16(9):2251–2261, 2007.

[17] S. Lankton and A. Tannenbaum. Localizing region-based active contours. *IEEE Transactions on Image Processing*, 17(11):2029–2039, 2008.

[18] C. Li, C.-Y. Kao, J. C. Gore, and Z. Ding. Minimization of region-scalable fitting energy for image segmentation. *IEEE Transactions on Image Processing*, 17(10):1940–1949, 2008.

[19] R. Luis-Garcia, R. Deriche, and C. Alberola-Lopez. Texture and color segmentation based on the combined use of the structure tensor and the image components. *Signal Processing*, 88(2):776–795, 2008.

[20] A. Mitiche and I. Ben Ayed. *Variational and level set methods in image segmentation.* Springer-Verlag, Berlin, Germany, 2010.

[21] A. Mosig, S. Jaeger, W. Chaofeng, I. Ersoy, S. K. Nath, K. Palaniappan, and S. Chen. Tracking cells in live cell imaging videos using topological alignments. *Algorithms in Molecular Biology*, 4:10p, 2009.

[22] D. Mumford and J. Shah. Optimal approximations by piecewise smooth functions and associated variational problems. *Communications in Pure and Applied Mathematics*, 42(5):577–685, 1989.

[23] S. Nath and K. Palaniappan. Adaptive robust structure tensors for orientation estimation and image segmentation. *Lecture Notes in Computer Science (ISVC)*, 3804:445–453, 2005.

[24] K. Ni, X. Bresson, T. Chan, and S. Esedoglu. Local histogram based segmentation using the Wasserstein distance. *International Journal of Computer Vision*, 84(1):97–111, 2009.

[25] S. Osher and R. Fedkiw. *Level set methods and dynamic implicit surfaces.* Springer-Verlag, New York, NY, USA, 2003.

[26] K. Palaniappan, F. Bunyak, P. Kumar, I. Ersoy, S. Jaeger, K. Ganguli, A. Haridas, J. Fraser, R. Rao, and G. Seetharaman. Efficient feature extraction and likelihood fusion for vehicle tracking in low frame rate airborne video. In *13th Int. Conf. Information Fusion*, 2010.

[27] K. Palaniappan, I. Ersoy, and S. K. Nath. Moving object segmentation using the flux tensor for biological video microscopy. *Lecture Notes in Computer Science (PCM)*, 4810:483–493, 2007.

[28] K. Palaniappan, H. S. Jiang, and T. I. Baskin. Non-rigid motion estimation using the robust tensor method. In *IEEE Computer Vision Pattern Recogition Workshop on Articulated and Nonrigid Motion*, pages 25–33, 2004.

[29] S. Prakash and S. Das. Segmenting multiple textured objects using geodesic active contour and DWT. In *Third International Conference on Pattern Recognition and Machine Intelligence (PReMI-07)*, pages 111–118, Kolkata, India, December 2007. Springer LNCS 4815 Eds.: A. Ghosh, R. K. De, Sankar K. Pal.

[30] V. B. S. Prasath. Color image segmentation based on vectorial multiscale diffusion with inter-scale linking. In *Third International Conference on Pattern Recognition and Machine Intelligence (PReMI-09)*, pages 339–344, Delhi, India, December 2009. Springer LNCS 5909 Eds.: S. Chaudhury, S. Mitra, C. A. Murthy, P. S. Sastry, Sankar K. Pal.

[31] B. Sandberg, T. F. Chan, and L. Vese. A level-set and Gabor-based active contour algorithm for segmenting textured images. Technical Report 02–39, UCLA CAM, 2002.

[32] M. A. Savelonas, D. K. Iakovidis, and D. Maroulis. Lbp-guided active contours. *Pattern Recognition Letters*, 29(9):1404–1415, 2008.

[33] L. Vese and T. F. Chan. A multiphase level set framework for image segmentation using the Mumford and Shah model. *International Journal of Computer Vision*, 50(3):271–293, 2002.

[34] X.-F. Wang, D.-S. Huang, and H. Xu. An efficient local Chan–Vese model for image segmentation. *Pattern Recognition*, 43(3):603–618, 2010.