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USE OF OBJECT SHAPE PRIORS FOR FRACTOGRAPHIC IMAGE SEGMENTATION

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An approach to efficient level-set model with shape priors for images segmentation is considered. The use of edge based level-set model in combination with principal component analysis (PCA) based shape priors for image segmentation is investigated. Shape priors are considered as a tool to cope with proper segmentation of overlapping or partially visible objects on input image. It is argued that in some cases consequent optimization of different groups of parameters can be advantageous in comparison to simultaneous optimization of all parameters. The approach was applied for segmentation of fractographic images obtained by scanning electron microscope (SEM). Experimental results for image segmentation using the level-set model with shape priors are presented.

Keywords: *image segmentation, level-set method, shape priors.*

ВИКОРИСТАННЯ АПРІОРНОЇ ІНФОРМАЦІЇ ПРО ФОРМУ ОБ'ЄКТІВ ДЛЯ СЕГМЕНТАЦІЇ ФРАКТОГРАФІЧНИХ ЗОБРАЖЕНЬ

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Розглянуто підхід до ефективної сегментації зображень моделями на основі level-set методу з використанням апріорної інформації про форму. Необхідність ускладнення моделей сегментації зображень використанням апріорної інформації про форму зумовлена особливістю фрактографічних зображень. До таких особливостей належать зашумленість зображення, часткова видимість і перекриття об'єктів на зображенні. Перелічені фактори часто унеможливлюють коректну сегментацію об'єкта, що базується на текстурних характеристиках зображення, або значеннях градацій сірого точок зображень. Використання апріорної інформації про форму накладає обмеження на форму сегметна зображення, яким виділяється об'єкт на вхідному зображенні. Особливу роль такі обмеження відіграють саме у місцях, де локалізація границі об'єкта є неоднозначною. У даній роботі досліджено поєднання level-set моделі, що базується на використанні контурів зображень, з використанням апріорної інформації про форму на основі методу головних компонент для сегментації зображень. Цей підхід застосовано для сегментації фрактографічних зображень, отриманих за допомогою сканівного електронного мікроскопа. Як відомо, моделі на основі level-set методу, що складаються з кількох компонент, поєднюють ці компоненти з вдповідними ваговими коеціентами. Значення цих вагових коеціентів і їх співвідношення вибрано залежно від конкретної задачі сегментації. Введення додаткової компоненти, зокрема апріорної інформації про форму об'єкта, вимагає ретельного вибору значень відповідних вагових коеціентів для коректної сегментації об'єкта. Виявлено, що у певних випадках почергова оптимізація певних груп параметрів може мати перевагу над одночасною оптимізацією всіх параметрів моделі. Подано експериментальні результати сегментації реальних фрактографічних зображень сканівного електронного мікроскопа.

Ключові слова: *сегментація зображень, level-set метод, апріорна інформація про форму.*

Introduction. Images produced by X-ray, MRI, SEM can contain noisy, overlapping or partially occluded objects. Automatized analysis of such images usually involves segmentation which in these conditions can be a very difficult task. One of the most problematic configurations is the case when overlapping objects share the same gray-scale levels of their pixels. In this case the task suffers from the lack of information required to draw true boundary of the objects. To fulfill proper image object segmentation an additional information should be added to the final model. One of such additions is prior information about the shape of the segmented object. In general case such task is challenging. But in case of objects with comparatively simple shapes the problem can be solved with less efforts.

General framework for image segmentation that accounts its shape consists of some well-known image segmentation technique with additional term to account shape information. Majority of image segmentation methods that allow such incorporation are optimization based techniques. Fitting shape to the image object is in general a complex problem. The main difficulty is the wide range of states that true shape of the object can be in. More formally, the object in image can have different scales, angle of rotation, position on the input image and possible variation of the shape. Finding all those parameters may be difficult and usually is done in iterative fashion. Thus, it is natural to incorporate shape information in well-known optimization based approaches. In this work we consider the level-set (LS) approach as a basic framework for image segmentation. It allows us to incorporate prior shape information as additional term in minimization functional.

Wide range of LS formulations were developed over the years to solve different image processing problems. Many researches successfully used the LS method in different fields and applications. There are three major branches of the LS methods with application to image segmentation: region-based models [1, 2], edge-based models [3] and hybrid models [4]. Edge-based models evolve LS function based on image edge information. Region-based models guide contour based on image region features. And hybrid model combines region- and edge-based information for evolution of the LS function.

One of the most known approaches for building shape prior terms is the one based on PCA transform. The popularity of this transform for shape modeling is its simplicity, low computational complexity and effectiveness for this particular task. Many papers are dedicated to the incorporation of shape priors to the image segmentation techniques. In [5] authors represented object shape with series of signed distance functions (SDF). The PCA transform then was applied to them to construct a shape model. This shape model was used in geometric active contour (GAC) [3] as a shape regularizing term. The problem with this approach consists in nonlinearity of SDF space, thus it is unable to reproduce all shapes with high precision. Nevertheless PCA based shape modeling is successfully used by many researchers. To cope with nonlinearity of SDF space in [6] the kernel PCA was used and authors concluded its superiority in comparison to linear PCA as the additional term in the GAC model to capture more complex behavior of shape variations. To overcome some limitations of PCA based approach in [7–9] authors used distance measure directly on reference shapes and LS function as shape prior. Also authors in [10, 11] used nonparametric approach of Kernel Density Estimation for shape modeling as a technique that allows to model a wide range of distributions.

The paper is organized as follows. In section II introduction to LS methods is presented. In section III approach to shape priors is discussed. Numerical results are provided in section IV.

The level-set methods for image segmentation. Let us represent a gray-level image as $u_0 : \Omega \to \Re$, where $\Omega \in \Re^2$ is image domain. LS method represents contour of the image object as zero crossing of the level-set function (LSF).

The foundation for the LS approach was introduced by Mumford and Shah [1]. They considered segmentation of input image u_0 as finding such contour C that separates image domain Ω on a sub-set of disjoint regions. In [1] the problem was formulated as minimization of the Mumford-Shah functional

$$E^{MS}(u,C)=\mu\cdot|C|+\lambda\int_{\Omega}|u-u_0|^2\,dxdy+\int_{\Omega\setminus C}|\nabla u|^2\,dxdy\,, \tag{1}$$

where $|C|$ represents the length of contour C, μ and λ are constant weights and u is a piecewise smooth approximation of image u_0 which is smooth inside each region and is discontinuous only on the set of boundaries C. The first right-hand side term in (1) regularizes the length of contour C. The second is the so called data term which forces u be as close as possible to the given image u_0. And the third term is the smoothing term, which forces u be smooth everywhere in $\Omega\setminus C$.

In [2] Chan and Vese simplified the Mumford-Shah functional and introduced its variational LS formulation for images with two segments as the following energy:

$$\begin{aligned}E^{CV}(c_1,c_2,\varphi)=\mu\int_{\Omega}|\nabla H(\varphi)|+\nu\int_{\Omega}H(\varphi)dxdy+\\+\lambda\int_{\Omega}|u_0(x,y)-c_1|^2\,H(\varphi)dxdy+\\+\lambda\int_{\Omega}|u_0(x,y)-c_2|^2\,(1-H(\varphi))dxdy\,,\end{aligned} \tag{2}$$

where $H(\varphi)$ is the Heaviside function, c_1 and c_2 are constants and $\varphi(x,y)$ is a LS function. In LS formulation contour C is represented by means of $\varphi(x,y)$ whose zero-level contour $C=\{(x,y)\in\Omega:\ \varphi(x,y)=0\}$ and it partitions the image domain into two disjoint regions $\Omega_1=\{(x,y):\ \varphi(x,y)>0\}$ and $\Omega_2=\{(x,y):\ \varphi(x,y)<0\}$. Model (2) is a particular case of the Mumford-Shah functional with piecewise constant u that can take only two values c_1 and c_2, thus it assumes that image I can be approximated by constants c_1 and c_2 in Ω_1 and Ω_2, respectively. The first two terms in (2) with a weight, regularizes the zero level contours, while the last two terms are the data fitting terms. Thus image u_0 segmentation is achieved by finding the LSF $\varphi(x,y)$ and constants c_1 and c_2 that minimize the energy $F(c_1,c_2,\varphi)$. This model is called a piecewise constant (*PC*) model.

The above models can be considered as a common framework for image segmentation and edge detection, active contours and denoising problems. They represent region-based models as they approximate image regions.

The most known edge-based LS approach is GAC [3]

$$E^{GAC}(C)=2\int_0^1|C'(s)|\,g(|\nabla I(C(s))|)ds\,, \tag{3}$$

where g is a stopping edge-function $g(|\nabla u_0|)=\dfrac{1}{1+|\nabla G_\sigma * u_0|^p}$. Minimization of functional (3) leads contour C to the edges of segmented image thus trying to separate object from the background.

The edge-based LS techniques are more stable to image intensity inhomogeneity and image distortions. But the main disadvantages of the edge-based LS techniques are sensitivity to initial conditions and boundary leakage in regions with weak object boundaries. These problems usually lead to unsatisfactory final segmentation of the input image. More satisfactory results can be achieved by enforcing some restrictions on the behavior of contour C evolution. One of such restrictions is the introduction of prior information about shape of the segmented object and directing the movement of the contour towards that desired shape. Incorporation of such prior knowledge is discussed in the next section.

Shape priors. Construction of shape prior suggests the existence of training shapes set. This set should contain shapes that reflect all possible shape variations of the object of interest. Having such set one can built a proper parameterized mathematical model of this shape and use it as additional term in segmentation models described in previous section.

Inspired by [7], the shape model was constructed based on SDF representation of training shapes with their consequent PCA processing. The PCA based shape model is characterized by mean shape $\bar{s}$ and set of parameters b. Fitting the shape $s = \bar{s} + Wb$ to the given LSF φ also requires estimation of affine transformations: translation, scale and rotation (t_x, t_y, m, θ). In [7] estimation of those parameters is obtained as the gradient descent solution to correspondent functional minimization. But being mathematically correct approach, its consistent performance require fine tuning of numerical implementation and its convergence is rather slow. In this work we estimated those parameters by a more direct approach [12] to avoid unnecessary computational complexity and difficulties with fine tuning.

Let us consider shape function $\psi\left(s, h\left(x,y\right)\right)$. It depends on shape s and set of transformations $\left(t_x, t_y, m, \theta\right)$ represented by $h\left(x,y\right)$. Shape function $\psi\left(s, h\left(x,y\right)\right)$ represents the closest distance from the point $\left(x,y\right) \in C$, $C = \left\{\left(x,y\right) \mid \varphi\left(x,y\right) = 1\right\}$, to the boundary of shape s.

Integration of $\psi^2\left(s, h\left(x,y\right)\right)$ along contour C defines the shape similarity functional which acts as shape prior and has the following form [7]

$$E_{shape} = \int_{\Omega} \psi^2\left(b, h\left(x,y\right)\right) |\nabla\varphi| \delta(\varphi) dxdy \,. \tag{4}$$

Applying the shape prior (4) the final image segmentation model is of the form

$$E = E_{image} + \lambda E_{shape} \,, \tag{5}$$

where $$E_{image} = E^{GAC} + \mu \int_{\Omega} gH(\varphi) dxdy \,.$$

The gradient descent solution to (5) is as follows

$$\frac{\partial\varphi}{\partial t} = \delta_{\varepsilon}(\varphi)\left[-\mu g - div\left(g\frac{\nabla\varphi}{|\nabla\varphi|}\right) - \lambda div\left(\psi^2\left(b, h\left(x,y\right)\right)\frac{\nabla\varphi}{|\nabla\varphi|}\right)\right]. \tag{6}$$

In most papers authors conduct simultaneous adjustment of all parameters at each iteration. In our experiments we noticed that such approach not always produced desirable results. For example, adjustment of shape parameters b from the start of evolution process is not effective and in some cases can slow the convergence of the model. It is more reasonable to start with mean shape $\bar{s}$ as initial and fix parameters b and at the beginning adjust only translation, scale and rotation. Only when these parameters change a little between iteration one can start updating parameters b. So it is proposed to conduct optimization of shape parameters b after LS function $\varphi(x,y)$ and parameters (t_x, t_y, m, θ) reached their optimal values. Also adjustment of parameter λ is very important for final result. Larger values of λ would force contour C toward the shape s, which can be useful for partially visible objects, noisy images etc. But larger λ also restricts contour C from deviation from s to accurately adjust to the object edges.

Majority of researchers adjust this parameter manually but it seems that adaptability of λ during segmentation process can be advantageous for successful convergence.

Experimental results. The model was tested on SEM fractographic images. The task consisted in segmentation of certain inclusions of spherical form. The problem arises when certain inclusions are overlapped with other parts of the steel structure. In such cases successful segmentation cannot be achieved by exploiting of only gray-level information.

Given that shape of the object expected to be circular, the shape model was built on a set of training ellipses to allow us some deviation from the perfect circle.

Fig. 1*a* contains a test image of the object with initial contour C. As it can be seen from Fig. 1*a* the object cannot be simply segmented based exclusively on pixel gray-level intensity information because it coincides with the background and part of it overlaps with vaguely visible border between them. Such case is a good example to demonstrate the usefulness of prior shape information for image segmentation.

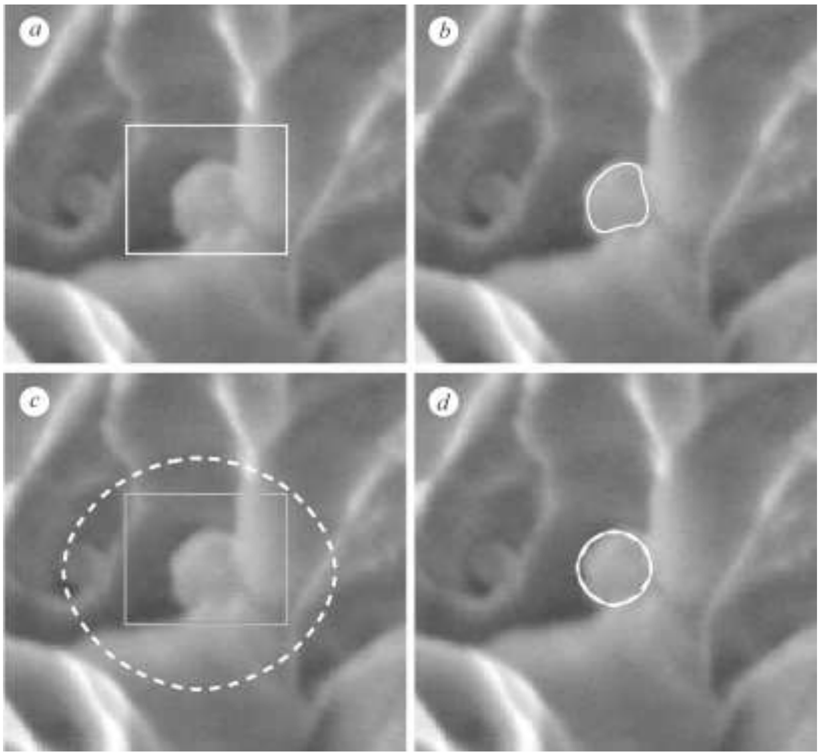

Illustration of the proposed approach: *a* – input image with initial contour; *b* – segmentation result by the conventional model (3); *c* – input image with initial contour and shape prior (dashed line); *d* – segmentation result by the proposed model (6).

The presented experimental results are obtained by model (6) with parameters $\mu = 1.0$ and $\lambda = 0.9$.

Fig. 1 (b) shows the segmentation result by the conventional model (3). As it can be seen from obtained results the model converges to the boundaries that differ from the object true size. Because the background and the object are partly overlapping there is no any distinguishable border between the background and the whole object segmentation process failed to segment objects properly.

Fig. 1*c* shows the initial contour and shape prior for model (6). Fig. 1*d* presents the segmentation result by the model (6). Even though the part of the object is occluded segmentation process managed to segment all true boundaries of the objects in a desirable way.

Conventional model (3) drives the evolution of contour C represented by $\varphi(x, y)$ towards image boundaries regardless of the object of interest shape. Thus, in presence of noise and occlusions contour C is likely to fail to find true object boundaries. The additional shape term (4) improves evolution of LS function by forcing contour C maintain its shape within certain boundaries.

CONCLUSION

In many practical applications it is not always possible to segment object of interest based strictly on the image pixel intensity values. In such cases segmentation model requires additional information for processing. In this paper shape priors as additional mechanism to drive segmentation process were discussed. Provided with shape priors information the original model produced better segmentation results in cases of object occlusion, presence of noise and in cases where parts of the object gray-levels coincide with the background. One can conclude that practical application of shape driven level-set method for fractographic image segmentation can be very useful. As numerical experiments show the use of such shape priors is well behaved for real image segmentation. Obtained experimental results showed efficiency and practical value of usage of the shape priors for difficult image segmentation tasks.

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