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Unsupervised multiphase segmentation: A recursive approach

Kangyu Ni [a], Byung-Woo Hong [b,*], Stefano Soatto [c], Tony Chan [a]

[a] Department of Mathematics, University of California, Los Angeles, CA, USA
[b] Department of Computer Science, Chung-Ang University, Seoul, Korea
[c] Department of Computer Science, University of California, Los Angeles, CA, USA

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ABSTRACT

We propose an unsupervised multiphase segmentation algorithm based on Bresson et al.'s fast global minimization of Chan and Vese's two-phase piecewise constant segmentation model. The proposed algorithm recursively partitions a region into two subregions, starting from the largest scale. The segmentation process automatically terminates and detects when all the regions cannot be partitioned further. The number of regions is not given and can be arbitrary. Furthermore, this method provides a full hierarchical representation that gives a structure of a given image.

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1. Introduction

Image segmentation aims to partition an image domain into different regions in a meaningful way. Edge-based active contours methods [8,4,9] pose segmentation as an energy minimization problem and use edge detection functions that are based on local features to evolve contours towards object edges. Region-based active contours models incorporate both regions and edges to find a partition. Our proposed algorithm takes a region-based active contours approach because it is robust to noise and based on more global features. One of the early efforts towards region-based active contours was made by the Mumford and Shah segmentation model [11], which approximates a given image by a piecewise smooth image. However, the posed energy minimization problem is difficult to solve. Zhu and Yuille [17] use a family of Gaussian distributions to describe each region's data, i.e. mean and variance, and determine the boundaries of regions by competing with neighboring regions to best fit models at the largest possible areas. Their proposed energy minimization problem is also in general difficult to solve. Chan and Vese [6] proposed to solve a two-phase piecewise constant segmentation model, which is a variant of the Mumford and Shah model. The novelty of Chan and Vese is the use of the level set method to represent the evolving curve. The minimization is conveniently obtained by the gradient descent of the Euler-Lagrange equation of the energy functional.

The extension from the celebrated Chan and Vese's two-phase segmentation model to multiphase segmentation is not so natural, which is due to the nature of level sets. Several attempts have been made towards this extension. Vese and Chan [16] use n level set functions to represent 2^n regions because each level set function splits the image domain into two. This method implicitly represents the constraint of disjoint regions so no coupling forces are needed in order to constrain disjoint regions. However, when the number of regions is not a power of two, extra work has to be done. Chung and Vese [7] use only one level set function but with level lines other than the zero-level line to represent contours. This method can represent n regions and the constraint of disjoint regions is also implicitly dealt with. However, their model cannot deal with triple junctions and the authors suggest combining their method with the Vese and Chan model to overcome this problem. Lie et al. [10] introduce to segmentation a piecewise constant level set function to represent each phase with a constant value. The piecewise constant constraint on the level set function is solved by using the augmented Lagrangian. Their level set method does not require re-initialization that is necessary for the classical level set method. However, extra work, as described in their paper, is needed for noisy images. The segmentation methods described above do not require any training set but the number of regions or at least an upper bound has to be given.

Brox and Weickert [3] use one level set function for each region to represent Zhu and Yuille's model. Brox and Weickert propose using a coupled curve evolution to solve this multiphase segmentation model but assume the number of regions is known. They also propose to automatically find the number of regions by a

* Corresponding author.
E-mail addresses: kni66@ucla.edu (K. Ni), hong@cau.ac.kr (B.-W. Hong), soatto@cs.ucla.edu (S. Soatto), TonyC@college.ucla.edu (T. Chan).

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coarse-to-fine strategy coupled with a hierarchical splitting. The authors apply a two-phase segmentation on a subregion, and if the Zhu and Yuille's energy functional is lowered, they continue this segmentation. This is repeated for all regions until the Zhu and Yuille's energy functional cannot be lowered. The number of phases obtained by this procedure is used in their multiphase segmentation model. Sandberg et al.'s piecewise constant segmentation model [13] automatically determines the number of regions and finds partitioning simultaneously. In the energy functional, they introduce a feature balancing term, the sum of all the inverse of region scales from each region, which is used to implicitly penalize the number of regions in addition to the total length of the boundaries. The *region scale* of a region is the quotient of its area and perimeter. Their model can be easily solved by a pixel-wise decision algorithm which implicitly deals with the disjoint constraint on all phases. This minimization method is very efficient but not robust to noise.

The followings are a few supervised multiphase segmentation models, although the focus of this work is an unsupervised method. Samson et al. [20] assume the number of regions is known, as well as the average intensity and variance in each region. Their model represents each region by a level set. Their proposed energy functional consists of three terms to enforce data fidelity, the regularity of the interface, and the constraints on no vacuum and overlapping of regions. Aujol and Chan [1,19] proposed a supervised classification framework for images with both textured and nontextured areas. The given image is first decomposed into a texture part and a geometric part. The data terms for the geometric part and texture part are treated by Samson et al.'s method and a wavelet-based level set evolution method [24]. Then, they use a logic framework to combine the results in a user definable way.

In this paper, we provide a spatial enclosure relationship between higher-level and lower-level regions so that one can analyze an image at a certain level of scale. *Scale* is related to contrast and region scale, and we use the definition of the TV scale in [18,21], which is defined as the time taken for a feature to disappear under the total variation flow. Tu and Zhu [15] consider segmentation a computing process rather than a vision task. The more one looks at an image, the more one sees. Therefore, segmentation results are not universal. We provide a "structure" of an image because that is how an image is usually interpreted. Following this idea, we propose to start from the coarsest partitioning and then refine each partitioning individually. Our proposed multiphase piecewise constant segmentation first applies the Chan and Vese model to partition an image domain into two and then recursively applies the Chan and Vese model in each partitioned region. This procedure gives a structure of an image implicitly utilizing the notion of "saliency" [14] that involves scale and intensity contrast in its determination. We additionally propose some stopping conditions to terminate the two-phase segmentation on the indicated region when it becomes meaningless to partition further. The stopping conditions use region scale and contrast to detect oversegmentation.

Fast Level Set Transform (FLST) [22,23] also provides a hierarchical representation of an image but is different from our algorithm. FLST uses a bottom-up region-growing algorithm to compute the family of lower (resp. upper) level sets with the increasing (resp. decreasing) inclusion property. With these inclusion properties, an image can be fully represented into a tree. Since their method is based on a local image feature, it is sensitive to noise; and therefore, a threshold is used to detect noise. Our proposed algorithm uses a top-down approach by recursively segmenting a region into two with a region-based model that is intrinsically robust to noise. In [22,23], an effective algorithm uses FLST and decomposes an image into a tree of shapes based on connected components of the level sets. A major advantage of this algorithm is due to the observation that with only intensity, the level set of an object may have undesired holes (closed level sets) inside their region; and their method is able to recognize the shape of the object without holes in it. Our algorithm does not assume this prior and on the other hand the segmentation process follows the notion of scale that is defined in the previous paragraph.

2. Two-phase piecewise constant segmentation on an indicated region

In this section, we first describe previous two-phase piecewise constant segmentation models and then present a natural extension to partition any given subregions that may be of arbitrary shapes. Let $f:\Omega\to[0,L]$ be the given grey-scale image. A two-phase piecewise constant version of the Mumford–Shah model [11] evolves a curve C towards the boundary between two regions and approximates f by two constants c_1 and c_2 inside the curve C and outside the curve C, respectively. The Chan and Vese model [6] is following energy minimization problem:

$$\inf_{C,c_1,c_2}\left\{E^1[C,c_1,c_2]=\int_C ds+\lambda\int_{inside(C)}(c_1-f(x))^2\,dx + \lambda\int_{outside(C)}(c_2-f(x))^2\,dx\right\}, \tag{1}$$

where the first term measures the total length of the curve C to penalize complicated interface between two regions and λ is a scalar parameter that controls the balance between regularization and data. This model can be represented in the following level-set formulation:

$$\inf_{\phi,c_1,c_2}\left\{E^1[\phi,c_1,c_2]=\int|\nabla H(\phi(x))|dx + \lambda\int H(\phi(x))(c_1-f(x))^2\,dx+\lambda\int[1-H(\phi(x))](c_2-f(x))^2\,dx\right\}, \tag{2}$$

where H is the Heaviside function and ϕ is a level set function [12] such that $\phi>0$ inside C and $\phi<0$ outside C. The minimization of this level set formulation can be solved naturally by the standard PDE method [6] and allows topological changes of the curve. However, this model is not convex and thus a reasonable initialization is necessary to avoid getting stuck at undesired local minima. Chan et al. [5] proposed a convex model that solves (1).

Based on [5], Bresson et al. [2] proposed a fast global minimization of the Chan and Vese model. There are two major advantages of their algorithm. The first is that the initialization can be arbitrary. The second is that the solutions can be obtained much faster than the standard PDE method. Bresson et al.'s model is the following minimization problem:

$$\min_{u,0\leqslant v\leqslant 1,c_1,c_2}\left\{E^2_\Omega[u,v,c_1,c_2]=TV_\Omega(u)+\frac{1}{2\theta}\|u-v\|_{L^2(\Omega)} + \lambda\int_\Omega v(x)(c_1-f(x))^2+[1-v(x)](c_2-f(x))^2\,dx\right\}, \tag{3}$$

where θ is small enough so that u and v are significantly close to each other, λ is a parameter controlling the data fidelity term, and the total variation of u is defined in the following:

$$TV_\Omega(u)=\sup\left\{\int_\Omega u\,\mathrm{div}\,p\,dx \,|\, p\in C^1_c(\Omega;\mathbb{R}^2):|p(x)|\leqslant 1,\ \ \forall x\in\Omega\right\}. \tag{4}$$

If $u^*=\operatorname{argmin}E^2_\Omega[u,v,c_1,c_2]$, the partition can be chosen to be, for instance, $\{u^*\geqslant 0.5\}$ and $\{u^*<0.5\}$. Let $r(x,c_1,c_2)=(c_1-f(x))^2-(c_2-f(x))^2$. The minimization is solved by alternating the following equations [2]:

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