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Image segmentation using fuzzy energy-based active contour with shape prior

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ABSTRACT

This paper presents a fuzzy energy-based active contour model with shape prior for image segmentation. The paper proposes a fuzzy energy functional including a data term and a shape prior term. The data term, inspired from the region-based active contour approach proposed by Chan and Vese, evolves the contour relied on image information. The shape term inspired from Chan and Zhu's work, defined as the distance between the evolving shape and a reference one, constrains the evolving contour with respect to the reference shape. To align the shapes, we exploit the shape normalization procedure which takes into account the affine transformation. In addition, to minimize the energy functional, we utilize a direct method to calculate the energy alterations. The proposed model therefore can deal with images with background clutter and object occlusion, improves the computational speed, and avoids difficulties associated with time step selection issue in gradient descent-based approaches.

1. Introduction

Active contour is one of the most powerful methods in image segmentation, and has been extensively used in a wide range of applications including computer vision, pattern recognition and medical imaging [1]. Active contour models (ACMs) [2] aim at finding a contour to represent the boundary of interested objects in an image by minimizing an energy functional. In ACMs, there has been a rising interest in implicit contour representations based on level set framework [3,4] that allows the contour to automatically change its topology, such as merge and split [4]. The level set approach has been adapted to image segmentation with low level feature information from images such as edge, and intensity. Commonly, relying upon image features, level set based active contour models can be categorized into two major classes: edge-based [5–7] and region-based models [8–12]. Edge-based models generally utilize image gradients to stop the evolving contours or surfaces on the object boundary. In region-based models, each region of interest is identified by using a certain region descriptor that guides the motion of the curves or surfaces. Compared to the edge-based models, the region-based models are less sensitive to noise and initial position of the contour. Furthermore, they can deal with images with weak boundaries.

In the region-based models, Mumford–Shah (MS) model [13] has been seen as the fundamental approach, in which the input image is approximated by piecewise smooth functions with regular boundaries. Later on, Chan and Vese minimized the energy functional of MS model within level set framework for piecewise constant [8] and smooth approximations [14] of the image to segment. Other works extending the Chan–Vese (C–V) model have been developed [15–18], in which the energy functionals are defined based on other intensity related information such as mean separation [15], histogram separation [16], and Bayesian model [17]. These models have been applied in a vast number of segmentation applications. However, they generally need to calculate the level-set curvature [19], and periodically re-initialize the level set to maintain the regularity of the level set function [20,21]. In addition, they often require a small time step to satisfy numerical stability constraints [22].

There have been many approaches to overcoming above drawbacks of conventional level set based active contour models. For example, Bernard et al. [19] proposed a variational B-spline level set model, in which the level-set function is expressed as the combination of continuous basic functions using B-splines. Xu et al. [23,24] incorporated ACMs into optimization tool of graph-cuts in segmentation. In an alternative approach, ACMs have been combined with fuzzy logic theory to enhance segmentation abilities [18,25,26]. In [25], Gibou et al. showed that with a suitable assumption, the Chan–Vese region-based active contour model in

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[8] could be reduced to K-means algorithm. They then proposed a fast hybrid K-means level set algorithm for segmentation. More recently, Krinidis and Chatzis [18] proposed a region-based active contour model based on fuzzy energy. In this model, the degree of membership function of each image point to the inside or outside the contour is incorporated into the energy functional. The energy alteration is then directly calculated, instead of solving the related Euler–Lagrange equation. By this way, the approach quickly converges to desired object boundary. In our recently work [26], the local fuzzy energy has been taken into account to handle intensity inhomogeneity in images.

Besides image feature based models discussed above, there has been a rising interest in encoding high level information into the energy functional. This stems from the fact that models based solely on image information like gradient and intensity might not be sufficient to facilitate the segmentation task in the presence of background clutter and object occlusion [27–29]. In such cases, introducing a prior knowledge about the shape of desired objects represents a natural way to solve the problems of clutter and occlusion. Towards this end, a common approach is incorporating a shape prior term into the variational cost functional [28]. The shape prior term in this context aims at penalizing the existence of non-overlapping areas between the evolving shape and the reference shape [30].

There have been many researches on shape prior based active contour models for segmentation in the literature. Among those, a vast number of works is devoted to representing the shapes by implicit functions, such as signed distance functions (SDFs). For example, Leventon et al. [31] integrated statistical shape prior into the geometric active contour models, in which the prior shapes are represented by SDFs. Then, they used the Principal Component Analysis (PCA) to estimate the shape features of aligned samples. Tsai et al. [32] used PCA to create a set of eigen-shapes, and then constructed the parametric shape model by a weighted sum of such eigen-shapes. Bresson et al. [27] also employed PCA to propose a shape prior model which consists of an average shape and the mode of variation on the space of implicit functions. In [33], Cremers et al. proposed a statistical shape prior, and introduced the kernel density estimation to the domain of level set based shape representations where prior shapes are represented by SDFs. In an alternative approach, instead of using signed distance functions, Dambreville et al. [34] proposed to build a space of familiar shapes by performing PCA on binary images. By this way, the approach enables constraining the contour evolution in a more faithful way to components of the training set.

A common issue in most shape prior based models is to account for possible transformations between the segmented shape and the reference one. Normally, the pose variation problems, such as rotation, scaling, and translation, between the target and reference shapes are expressed by a set of coupled partial differential equations (PDEs) [30,35]. The pose parameters are then computed by solving Euler–Lagrange equations via the gradient descent. This approach often suffers from challenges associated with choosing suitable time steps for each equation of pose parameters to satisfy severe numerical stability constraints. In addition, the order of parameter iterations is also an issue as pointed out by Cremers et al. [33].

In this paper, to handle challenges in shape prior based segmentation, we propose an alternative approach to avoid solving partial differential equations in both handling shape variations and minimizing the energy functional. In more detail, we utilize the theory of moment invariants and shape normalization [36,37], which accounts for affine transformation, to align the shapes. By this way, we could directly compute the pose transformation, instead of solving a set of coupled partial differential equations as in the gradient descent approach. In the proposed energy functional, we introduce a shape prior into the fitting terms of fuzzy energy-based ACM [18]. To minimize the energy functional, instead of solving the Euler–Lagrange equation of the underlying problem, we utilize the fast algorithm for level set based optimization [18,22] to directly calculate the alterations of the energy. The proposed model is therefore able to segment images even in the presence of clutter and occlusion in an efficient way. In addition, the model significantly improves the computational speed, and avoids difficulties associated with time step selection which is an issue in gradient descent based approaches.

The remainder of this paper is organized as follows. Section 2 introduces the moment-based shape descriptor and normalization. Section 3 reviews the active contour segmentation. The description of the proposed shape prior model for image segmentation is presented in Section 4. The implementation and experimental results are given in Section 5. We end the paper with a brief conclusion in Section 6.

2. Shape description and normalization

2.1. Moment-based shape description

Image moments play an important role in object representation and shape analysis. Especially, they are useful to describe objects after segmentation. Inspired by Hu [38], the use of moments is straightforward if we consider an image as a two-dimensional density distribution function $f(x,y)$. The set of geometric moments of a two-dimensional density distribution function $f(x,y)$ is commonly defined as

$$m_{pq} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x^p y^q f(x,y)dxdy, \tag{1}$$

where p and q are nonnegative integers, and $(p+q)$ is the order of moments.

The central moments, which are invariants to translation, can be defined as

$$\mu_{pq} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} (x-\bar{x})^p (y-\bar{y})^q f(x,y)dxdy, \tag{2}$$

where $\bar{x} = m_{10}/m_{00}$ and $\bar{y} = m_{01}/m_{00}$ are coordinates of the centroid.

If we consider a shape as a binary image, these moments naturally provide descriptors of the shape, such as: the zero order moment, m_{00}, presents the area, the first order moments present the centroid, and the second-order moments characterize the size and orientation of the object.

2.2. Shape normalization algorithm

Shape normalization procedure [36,37] aims at making the shape invariant under translation, scaling, and rotation. Main steps for shape normalization can be summarized as follows:

Step 1. Compute covariance matrix **M** *of the original shape.*

From central moments in (2), calculate the covariance matrix **M** as

$$\mathbf{M} = \begin{bmatrix} \mu_{2\ 0} & \mu_{1\ 1} \\ \mu_{1\ 1} & \mu_{0\ 2} \end{bmatrix}. \tag{3}$$

Step 2. Align the coordinates with the eigenvectors of **M.**

Calculate eigenvalues of covariance matrix **M**, λ_1 and λ_2. Let $\mathbf{e_i} = \left[e_{ix} e_{iy}\right]^T$ be the eigenvector associated with λ_i $(i = 1, 2)$. The eigenvectors are computed as

$$\mathbf{e_i} = \begin{bmatrix} e_{ix} \\ e_{iy} \end{bmatrix} = \left[\mu_{11}\Big/\sqrt{(\mu_i-\mu_{20})^2+\mu_{11}^2}\ (\lambda_i-\mu_{20})\Big/\sqrt{(\mu_i-\mu_{20})^2+\mu_{11}^2}\right],\quad i=1,2. \tag{4}$$