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A level set method with shape priors by using locality preserving projections

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ABSTRACT

A novel level set method (LSM) with the constraint of shape priors is proposed to implement a selective image segmentation. Firstly, the shape priors are aligned by using image moment to deprive the spatial related information. Secondly, the aligned shape priors are projected into the subspace expanded by using locality preserving projection to measure the similarity between the shapes. Finally, a new energy functional is built by combing data-driven and shape-driven energy items to implement a selective image segmentation method. We assess the proposed method and some representative LSMs on the synthetic, medical and natural images, the results suggest that the proposed one is superior to the pure data-driven LSMs and the representative LSMs with shape priors.

1. Introduction

Image segmentation is an important bridge connecting the low-layer image processing and the high-layer image analysis and understanding [1]. In past several decades, numerous segmentation methods based on different theories, *e.g.*, graph-based ones [2] and PDE-based ones [3], have been proposed. Graph-based image segmentation methods map an image onto a graph, and depict the relationship between pixels by weighted edges. In such way, image segmentation problem is modeled as a procedure of partitioning a graph into a set of sub-graphs, each of which represents a meaningful object in the image. Then, the segmentation problem is solved in a spatially discrete space. Some graph-based methods, *e.g.*, minimal spanning tree based ones [4], graph-cut based ones [5,6], and shortest path based ones [7] are proposed and achieve better performance. However, the graph-based segmentation methods tend to partition small regions from images [8]. As an alternative, active contour models (ACMs) based on partial differential equations (PDEs) involves some characters of objects' outline, *e.g.*, closure and smoothness, into segmentation into energy function, and realize segmentation by minimizing energy function. Up to now, ACMs have become a popular technique for image segmentation.

Snake algorithm [9,10] is the pioneer of ACMs, and has been widely used in image segmentation, object recovery, etc. Even so, Snake cannot well handle the topological changing of evolving curve, *i.e., splitting and merging*. Osher and Sethian [11] then proposed a signed distance function (SDF) defined in higher dimensional space and implicitly described a closed planar curve by the zero level set of SDF. Allowing the evolving curve to change its topology [12] SDF greatly facilitates the comparison of different curves in topology. Following the work of Osher and Sethian [11], Malladi et al. [13] developed a formula for shape recovery; Caselles et al. [14] and Chopp [15] also designed some derived PDEs from the associated energy functional. These three methods started the edge-based LSMs which are featured with the image gradient based stopping force. Yet, this kind of edge-based stopping force is not robust against noise and cannot well handle the weak boundaries of complex structures. Chan and Vese [16] designed a region-based stopping force based on the Mumford-Shah model [17,18]. It boosted the region-based approaches and was successively extended to vector-valued images [19], tensor-valued images [20,21], multi-phase level sets [22], and piecewise smooth approximation [23]. Additionally, Rousson et al. [24] and Chen et al. [25] incorporated the region information by applying maximum a-posteriori (MAP) for image segmentation. Li et al. designed a regularized term in energy function to keep LSF being signed during evolution [27,28]. Wang et al. combined the local and global cues of images to improve the performance on weak boundaries, and achieved better result [26].

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To overcome the inhomogeneity of objects, Li et al. proposed a local clustering criterion function [29].

Both the edge-based [11,13–15] and the region-based [16,19,21] LSMs achieved success on different images, however, they just consider low level features. That means that the curve's revolution is just driven by image data without any high level shape knowledge. Consequently, it is difficult for them to well handle the segmentation of broken objects, the overlapped objects and the objects in complex background. LSMs with shape priors, to some extent, could improve the segmentation performance on these objects. According to the way of incorporating external constraint, the LSMs with shape priors can be divided into two categories, *i.e.*, the parametric model and the non-parametric model.

Extending the work of Chen et al. [25], Chan and Zhu [30] defined a shape distance function and proposed a LSM with a single shape prior. This distance function was also used in [31] which added a dynamic label function into the energy functional. These two models, however, just consider the distance between the current shape and the shape prior, and cannot be directly applied to the case with multiple shape priors. Fahmi and Farag [32] extended [30] to the multiple level set functions with multiple shape priors, but there is still one shape prior for one level set function. Tsai et al. [33,34] utilized principle component analysis (PCA) [35] on the shape priors and obtained a series of eigen shapes (*i.e.*, eigen vectors in matrix form). The linear combination of eigen shapes is used to approximate the shape of current object, however, the problem is that this linear reconstruction does not always correspond to an effect shape [42]. Rousson and Paragios [24] employed the shape-to-area principle for the shape alignment, and then built the shape-driven energy item along the thought of Tsai et al. [33,34]. Hossam [36] presented a more complex transformation with more motion parameters to improve the work of [33,34]. Considering these methods all minimize the energy functional by optimizing the affine parameters and/or local motion parameters (*e.g.*, the coefficients of PCA), we classify them together as the parametric model with shape priors. The main shortage of the parametric model is that the evolution process is difficult to converge when the number of parameters is increasing. Additionally, in practice, the step of parameters for gradient descent algorithm is hard to determine.

Instead of optimizing the motion parameters, the non-parametric model with shape priors employs statistical techniques to involve the shape priors into the curve evolution. Leventon et al. [37] performed PCA on the aligned shape priors. Under the Gaussian distribution assumption, MAP then was utilized to design the shape-driven energy item. Following the work of Leventon et al., Derraz et al. [38] and Samuel et al. [39] replaced PCA with Kernel-PCA to capture the real distribution structure in low-dimensional space. Prisacariu et al. assumed the shape priors distribute on a low-dimensional manifold by which a similarity measure is designed [40]. Chen et al. utilized sparse representation to code shape priors instead of PCA/KPCA [41]. Cremers et al. [42] made an intrinsic alignment on the shape priors, and then employed kernel density estimation (KDE) to build a statistical-based shape energy term. The intrinsic alignment does not need to iteratively compute the parameters of affine transformation like in [43], and the shape-driven energy item abandons the motion parameters in parametric models [33,34,36]. However, there are some problems worth considering as follows. Firstly, the intrinsic alignment cannot array the shape priors along a specific orientation, which causes that these method cannot work well when the shape priors are not parallel to the given shape. Secondly, the shape priors sparsely distributing in a high-dimensional space makes it difficult to obtain a real distribution structure.

To overcome these two problems, we propose a novel LSM with shape priors. Inspired by [42], the shape priors are rearranged based on the image moments. For the case with multiple shape priors, Locality Preserving Projections (LPP) [44] is utilized to reduce the dimensionality of shape priors and to capture their real statistical distribution in a low-dimensional space. The proposed model with shape priors has three advantages as follows. Firstly, we use the moment-based alignment based on the intrinsic alignment to deprive the shape priors of scale, position and angle information, which Secondly, the statistical distribution of the shape priors is observed in a low-dimensional subspace expanded by using LPP. The expanded subspace preserves the locality relationship of shape priors in observation space, and contributes to modeling the statistical distribution more accurately. A direct result is that the LPP based shape-driven energy term can well handle the shape with non-smooth outline. The proposed method is compared with some representative LSMs [16,39,42], and the comparison results show that the proposed method obtains a competitive performance than the three methods.

The rest of this paper is organized as follows. Section 2 revisits the previous related work, Section 3 presents the proposed method including two cases, *i.e.*, single shape prior and multiple shape priors, respectively. Section 4 evaluates the performance of the proposed method comparing with other LSMs [16,42] on the artificial images, natural images and medical images. Section 5 is the conclusion.

2. Previous related work

Chan and Vese [16] proposed a region-based LSM by using Mumford-Shah model [17,18]. This method is robust against noise and usually combined with the shape-driven energy item to implement a selective image segmentation. For the convenience of the hereinafter discussion, here we briefly introduce the Chan-Vese method [16] whose energy functional is defined as

$$\begin{aligned} E(\phi) = \mu \int_{\Omega} \delta(\phi)|\nabla\phi|dxdy + \nu \int_{\Omega} H(\phi)dxdy \\ +\lambda_1 \int_{inside(C)} |I-c_1|^2 dxdy \\ +\lambda_2 \int_{outside(C)} |I-c_2|^2 dxdy, \end{aligned} \tag{1}$$

where Ω denotes the image domain; c_1 and c_2 are the grayscale averages inward and outward the evolving curve, respectively; $H(\cdot)$ is the Heaviside function and $H(\phi)$ hence denotes the region enclosed by the evolving curve. The first term is an internal energy term making the evolving curve smooth enough. The second term is usually being omitted for having same effect with the first term [19]. The last two terms are the fitting errors between the image to be segmented I and the piecewise constant approximation I', *i.e.*,

$$I' = c_1 H(\phi) + c_2(1 - H(\phi)). \tag{2}$$

It is not difficult to see that the essence of Chan-Vese method [16] is seeking an optimized piecewise constant representation for the given image under a geometrical constraint, *i.e.*, the evolving curve, *i.e.*, the first term in Eq. (1), is kept smooth. There are some variant expansions of the Chan-Vese method [16], for example, Rousson et al. [24] and Chen et al. [25] employed MAP to design the external energy item. Since the Eq. (1) is most simple and representative, it is usually employed to build more complex energy functional.

For LSMs with shape priors, Leventon et al. [37] applied PCA to the aligned shape priors and obtained a series of eigen shapes and one mean shape. Using the distance of a current shape and the linear combination of these shapes, Leventon develop the shape-driven energy item. Whereas, PCA assumes that the shapes are Gaussian distribution which is usually not satisfied. Cremers et al. [31] utilized a moment-based alignment method to compute the affine parameters, and KDE to estimate the probability without the assumption of Gaussian distribution.