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Iterative image segmentation with feature driven heuristic four-color labeling

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ABSTRACT

Multilabel segmentation is an important research branch in image segmentation field. In our previous work, Multiphase Multiple Piecewise Constant and Geodesic Active Contour (MMPC-GAC) model was proposed, which can effectively describe multiple objects and background with intensity inhomogeneity. It can be approximately solved with Multiple Layer Graph (MLG) methods. To make the optimization more efficient and limit the approximate error, four-color labeling theorem was further introduced which can limit the MLG within three layers (representing four phases). However, the adopted random four-color labeling method usually provides chaotic color maps with obvious inhomogeneity for those semantic consistent regions. For this case, a new and alternative method named heuristic four-color labeling is proposed in this paper, which aims to generate more reasonable color maps with a global view of the whole image. And compared with the random four-color labeling strategy, the whole iterative algorithm based on our method usually produces better segmentations with faster convergence, particularly for images with clutters and complicated structures. This strategy is a good substitute for random coloring method when the latter produces unsatisfactory messy segmentation. Experiments conducted on public dataset demonstrate the effectiveness of the proposed method.

1. Introduction

Image segmentation is a fundamental and challenging task in computer vision society, which plays an important role in many senior applications. Because of the convenience of unsupervised method, it receives more attention recently. However, considering the complexity of natural scene, the performance of totally unsupervised segmentation methods is still far from satisfactory.

In our previous work [1], an unsupervised image segmentation method based on Multiphase Multiple Piecewise Constant and Geodesic Active Contour (MMPC-GAC) model is proposed. To provide an efficient approximate optimization with Multiple Layer Graph (MLG) and reduce the approximate error of optimization, four-color labeling is introduced into the optimization iteration to limit MLG within three layers (representing four phases). But for those images with clutters and complicated structures, the randomness of original four-color labeling process usually produces chaotic color maps, which may lead to slow convergence and unsatisfactory segmentation. To solve these problems, we introduce a region adjacency cracking method to adaptively loosen the color labeling constraints. Moreover, a heuristic four-color labeling algorithm is proposed to establish global consistency for those regions of homogeneous appearance. We report both qualitative and quantitative results over public image datasets. The results with comparisons show that the proposed labeling method is a good substitute and improvement for random coloring method, especially for those images with clutters and complicated structures.

The rest of this paper is organized as follows. After a brief review of the related literatures in Section 2, we first revisit the four-color labeling assisted MMPC-GAC model for image segmentation in Section 3. And then the proposed feature driven heuristic four-color labeling method is introduced in Section 4. The experiments with qualitative and quantitative analysis are given in Section 5. Finally, we conclude our paper and give discussion about the future work in Section 6.

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2. Related works

Image segmentation algorithms can be roughly divided into three categories according to the role of user-provide prior knowledge in the approach [2], i.e., unsupervised methods, semi-supervised methods and supervised methods. Actually, all these three kinds of methods are correlated with each other and the border lines are not very clear. The unsupervised methods segment images without any human intervention [3–6]. Methods processing images with coarse priors, such as casual captions [7–9], user scribbles and annotations [10–12] can be viewed as semi-supervised methods. And more recently, with the advent of large annotation dataset, supervised methods receive great development [13,14]. These methods achieve good performance since they learn superior target-specified models with those carefully annotated datasets. Since we focus on unsupervised segmentation in this paper, we only give a review of unsupervised methods in this section. A more comprehensive review of image segmentation works can be found in [2].

Segmentation problems are essentially clustering problems, which aim to group the pixels into local homogenous regions. K-means, mean-shift [3] region merging [15,16], region splitting [17,18] and more recent works [19–21] are all typical examples for clustering based methods. Specifically, K-means is a parametric approach which requires a prior knowledge of the number of clustering centers. While mean-shift, region merging, splitting methods and [19–21] are all non-parametric approaches, which need no assumptions about the number of centers or feature distributions. Besides clustering based methods, graph based methods also receive great attention, such as graph-based image segmentation [4,5,22], ratio cut [23], normalized cut [24], average cut [25], segmentation with spanning tree presentation [26], etc. More recently, Wang et al. [27] introduced normalized and average tree partitioning methods to perform normalized and average cut over a tree. Saglam and Baykan [28] used Prim's sequential representation of minimum spanning tree and presented a new cutting criterion for image segmentation. Besides, some approaches based on random walk model [29,30] also receive good performance.

The aforementioned methods are all defined in discrete domain. Actually, continuous models [1,31–36] are also widely used in image segmentation society. Mumford–Shah model [31] for segmentation aims to seek piece-wise smooth approximation and minimal edge cost. By assuming the local regions are piecewise constant, Chan–Vese model [32] introduces level set representation to bridge the gap between the theoretic formulation of [31] and optimization difficulty in practice, which further simplifies Mumford–Shah model. In [35] and [1], the piecewise constant model is further extended to Multiple Piecewise Constant model (MPC) [35] and Multiphase Multiple Piecewise Constant model (MMPC) [1] to adapt to more complex situations. We will give more detailed description about this model in the following section.

3. MMPC-GAC model based image segmentation with four-color labeling

3.1. MMPC-GAC model

Snake model [37] and Mumford–Shah model [31] are widely used variational framework in image segmentation society. And their simplified version, called Geodesic Active Contour (GAC) [38] and piecewise constant models [32,35], are popular in practical application. In our previous work [1], to describe the targets and backgrounds with appearance inhomogeneity as well as to keep a better boundary capturing ability, an advanced model named MMPC-GAC is established by combining the Multiphase Multiple Piecewise Constant (MMPC) model and GAC model. In this section, for the sake of descriptive integrality, we will first give a brief review of the MMPC-GAC model.

The energy formulation of MMPC-GAC model can be written as follows:

$$E^{MMPC-GAC}(c, C) = E^{MMPC} + \nu E^{GAC}, \tag{1}$$

$$E^{MMPC} = \sum_{l=1}^{m} \int_{\Omega_l} \min_{k=1\cdots n_l} (u_0(x,y) - c_l(k))^2 dxdy, \tag{2}$$

$$E^{GAC} = \oint_{L(C)} g(C(s))ds, \tag{3}$$

where $u_0(x, y)$ is the feature of the given image at point (x, y), $c_l(k), k = 1, \dots, n_l$ are the multiple piecewise constant functions that fit the multiple phases $\Omega_l, l = 1, \dots, m$. C is the segmentation curve whose length is $L(C)$, $g(u_0) = \exp(-\beta|\nabla u_0|)$.

This formulation is still defined in the continuous domain which cannot be directly applied in image domain. Accordingly, the discrete version of Eq. (2) can be expressed as

$$E_D^{MMPC} = \sum_{l=1\cdots m} \sum_{p\in P} \min_{k=1\cdots n_l} (u_0(p) - c_l(k))^2 \psi(\varphi(p) - l) \tag{4}$$

where p is from the set of image grid points P, $\{\varphi(p)|\varphi(p) \in \{1, \dots, m\}\}$ is the label function, $\psi(x)$ is an indicator function which is defined as

$$\psi(x) = \begin{cases} 1, & x = 0, \\ 0, & \text{otherwise}. \end{cases} \tag{5}$$

If we divide each P_l, which is defined on phase Ω_l, into n_l subgroups $\{P_{lk}, k = 1, \dots, n_l\}$ with K-means, and assign label $\pi_l(p) = k$ to pixels in P_{lk}, then we can get the piecewise constant $c_l(k)$ defined on P_{lk} as

$$c_l(k) = \frac{\sum_{p\in P_l} u_0(p)\psi(\pi_l(p) - k)}{\sum_{p\in P_l} \psi(\pi_l(p) - k)}, \tag{6}$$

where $l \in \{1, \dots, m\}$, $k \in \{1, \dots, n_l\}$.

The discrete formulation of $E^{GAC}(C)$ can be expressed as

$$E_D^{GAC} = \sum_{p\in P} \sum_{q\in N(p)} \omega_{pq} \exp(-\beta|u_0(p) - u_0(q)|)(1 - \psi(\varphi(p) - \varphi(q))), \tag{7}$$

where q belongs to the 4 or 8 neighborhood of pixel p along the segmentation curve, ω_{pq} is determined by the direction of edge (p, q) and the neighbor system N. And then, the overall discrete formulation of MMPC-GAC model can be written as follows:

$$\begin{aligned} E_D^{\text{Overall}}(c, \varphi) = & \sum_{l=1\cdots m} \sum_{p\in P} \min_{k=1\cdots n_l} (u_0(p) - c_l(k))^2 \psi(\varphi(p) - l) \\ & + \nu \sum_{p\in P} \sum_{q\in N(p)} w_{pq}(1 - \psi(\varphi(p) - \varphi(q))), \end{aligned} \tag{8}$$

where $w_{pq} = \omega_{pq} \exp(-\beta|u_0(p) - u_0(q)|)$.

3.2. Optimization with multiple layer graph and four-color labeling

Actually, Eq. (8) formulates a multilabel Potts model, which cannot be exactly optimized with multiple layer graph methods [39,40]. In [1], we adopt them to achieve the approximate optimization of Eq. (8) by minimizing the following formula

$$\begin{aligned} E^{MLG}(c, \varphi) = & \sum_{l=1\cdots m} \sum_{p\in P} \min_{k=1\cdots n_l} (u_0(p) - c_l(k))^2 \psi(\varphi(p) - l) \\ & + \nu \sum_{p\in P} \sum_{q\in N(p)} w_{pq}|\varphi(p) - \varphi(q)| \end{aligned} \tag{9}$$