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A simultaneous cartoon and texture segmentation method within the fuzzy framework

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ABSTRACT

This paper presents a new image segmentation method called simultaneous cartoon and texture segmentation (SCTS). The proposed method takes advantage of the decomposition of images into the cartoon and texture components and their respective properties. In the proposed model, each region is represented by a fuzzy membership function (FMF), and two data fidelity terms are jointly defined to measure the conformity of cartoon and texture components within image regions. In order to efficiently solve the proposed model, a fast alternative iteration algorithm for SCTS is presented. Most importantly, the proposed method has good selectivity to patterns of cartoon, texture and noise, which makes it increase the robustness and produce better results than the classical methods. Experimental results show that the proposed method has very promising segmentation performance.

1. Introduction

Image segmentation is a fundamental problem in image processing and computer vision. So far, image segmentation is still a challenging task due to the complexity of images. In recent years, many methods have been proposed for image segmentation task, such as variational methods [1–9], clustering-based methods [10–13] and graph-cut-based methods [14,15], etc. In this paper, we formulate the segmentation problem in the variational framework. The conventional variational models [1–5] assume that the sub-regions of images are uniform and homogeneous attributes. A piecewise smooth or local piecewise smooth function is usually used to approximate a given image. So, the conventional variational models have obtained promising performance in segmenting cartoon-like images. However, in many real situations, images may include the cartoon component, the texture component, the intensity inhomogeneities variation and the noise. The presence of these different patterns violates the piecewise smooth or local piecewise smooth assumption. As a consequence, some classical variational models usually fail in handling the segmentation of texture and illumination inhomogeneities images. To address these problems, some models have been extensively studied [6–9]. Although these methods improve image segmentation performance in many cases, their use is limited to images which accord with the assumption of piecewise smooth or local piecewise smooth. Hence, it is unsuitable for these methods to segment an image with different visual patterns. Real images usually have two components called the cartoon and texture components. Different components have different characteristics. The cartoon component is a simplified piecewise smooth or constant image while the texture component consists of oscillatory content or noise. The task of image decomposition aims to separate the cartoon and texture features of an image (different layers) [16–22]. Image decomposition has become a valuable tool in image processing. It has also been an active topic, due to its applications to image restoration [23], image inpainting [24], image classification [25] and image registration [26], etc. In this paper we apply image decomposition method to image segmentation task.

The authors in [27] present an image segmentation method which combines image decomposition and spectral cuts. Weights of the affinity graph are computed by using the cartoon component of the image. According to user interaction, the weights of the affinity graph are updated by taking into account the texture component of the image. Their method reduces the sensitivity to the texture and noise components, and produces smoother segmentation curves. Very recently, the authors in [28] propose an image decomposition based image segmentation method. In their method, for images of fabric texture, only the cartoon component is considered as the essential features of images, while the texture component is regarded as "texture noise". By taking into account the morphological diversity of images, the author in [29] presents an image segmentation method by learning the morphological diversity. Although the method in [29] can adaptively learn different morphological contents, the cartoon component is only used to measure the conformity within the image region without

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considering the contributions of the texture component for image segmentation. Hence these methods are not simultaneously cartoon and texture segmentation methods.

For general images, there is no doubt that both the cartoon component and the texture component are the important features. Hence, their contributions for image segmentation should not be ignored. This paper proposes a simultaneous cartoon and texture segmentation method that takes into account the basic properties of both the cartoon component and the texture component. The main idea is to segment a given image according to the two different layers features of the image modeled by the piecewise smooth assumption and the parametric probability model. In the proposed model, the fuzzy membership functions regularized by wavelet are used to measure the association degree of each pixel to all regions. By using two data fidelity terms, the cartoon and texture components are jointly considered to evaluate the performance of the label assignment.

This paper is organized as follows. In Section 2, we introduce a classical image decomposition method for the following discussion. Section 3 presents the proposed image segmentation model and algorithm. In Section 4, the experimental results show that the proposed method has good selectivity to patterns of cartoon, texture and noise, which makes it increase the robustness and produce better results than the classical methods. Finally, we conclude the paper in Section 5.

2. Image decomposition

In this section, we will briefly review some image decomposition approaches and an image decomposition model that is related to our method. In recent years, many image decomposition methods have been proposed. These methods can be roughly classified into the following three categories: norm-based methods [16–19], filter-based methods [20], sparse representation-based methods [21,22]. Norm-based methods use different norms to model the cartoon and texture components. Filter-based methods usually use a pair of filters to remain or remove the cartoon or texture component. Sparse representation-based methods select or learn two dictionaries to represent the cartoon and texture components respectively under sparse constraints. In this paper, we use norm-based method to decompose a given image. Although other image decomposition methods also can be used in the proposed method, norm-based methods have the advantages of easer implementation and higher efficiency. In this paper, a given image f is modeled as $f = u + v$, where u is the cartoon component, modeling sharp edges, and v is the texture component, modeling the oscillating pattern. Osher et al. [17] propose that the cartoon component is modeled by total variation norm and the oscillating texture component is modeled by the H^{-1}-norm, and discussed the following minimization problem:

$$\inf_{u \in BV} \left\{ D(f, u, v) = |\nabla u|_1 + \xi \left\| v \right\|_{H^{-1}}^2 \right\}, \quad \mathrm{s.t.} f = u + v, \tag{1}$$

where $|\nabla u|_1 = \int_\Omega |\nabla u|$ is the total variation of u, $\left\| v \right\|_{H^{-1}}^2 = \int_\Omega \left| \nabla(\Delta^{-1} v) \right|^2$ is the H^{-1}-norm of v, and ξ is a scale parameter controlling the scale of image decomposition. The model (1) has the explicit Euler–Lagrange equation. We can obtain its solution by the corresponding diffusion flow. Let $D'(f, u, v) = 0$, the Euler–Lagrange equation is

$$2\xi \Delta^{-1}(f - u) = \mathrm{div}\left(\frac{\nabla u}{|\nabla u|} \right), \left. \frac{\partial u}{\partial n} \right|_{\partial\Omega} = 0, \left. \frac{\partial \mathrm{div}\left(\frac{\nabla u}{|\nabla u|} \right)}{\partial n} \right|_{\partial\Omega} = 0. \tag{2}$$

Multiplying Laplacian operator Δ on the both sides of (2), we have

$$2\xi(f - u) = \Delta \mathrm{div}\left(\frac{\nabla u}{|\nabla u|} \right), \left. \frac{\partial u}{\partial n} \right|_{\partial\Omega} = 0, \left. \frac{\partial \mathrm{div}\left(\frac{\nabla u}{|\nabla u|} \right)}{\partial n} \right|_{\partial\Omega} = 0. \tag{3}$$

Hence, we obtain the corresponding diffusion flow

$$\frac{du}{dt} = -\frac{1}{2\xi} \Delta \mathrm{div}\left(\frac{\nabla u}{|\nabla u|} \right) + (f - u). \tag{4}$$

The diffusion will be used as a preprocessing step in our method.

3. The proposed method

This section gives the features description of cartoon and texture components firstly, and then presents the proposed segmentation model and an efficient well-designed algorithm for SCTS.

3.1. The feature description

Image priors play a central role in image processing. For the cartoon component, it can be approximated by a piecewise constant function c_i because the cartoon component is a simplified piecewise smooth image. For the texture component, we employ the statistical property as a region characterization. Note that the selection of statistical models should be dependent on different applications. This paper adopts the standard Gaussian distribution. However, the standard Gaussian distribution cannot directly used to model texture pattern in theory and practice [14]. To describe texture information, the texture component v is represented by a texture descriptor which can be based on filter bank response or transform domain methods, such as Gabor filtering [10], structure tensor [30], wavelet, wavelet package and principal component analysis (PCA), etc. In this work, we use PCA to obtain the texture descriptor. Because an upper bound of the true coding length for the PCA features of texture can be obtained under Gaussian distribution, the PCA features of texture can be modeled by Gaussian distribution [14]. Using Gaussian distribution, we can obtain the closed form solutions for the model parameters estimation (see (16) and (17)) which enables us to implement a very efficient numerical scheme. Write the texture descriptor as $V = \{G_j v\}_{j=1,2,\ldots,M}$, where M is the feature dimension index, and $G_j v$ denotes the jth PCA component. Note that the texture descriptor V is obtained by PCA projecting the texture component v rather than the original image f, see the experimental setting. We further assume that for a given region Ω_i, the texture descriptor V is a independent and identically distributed (i.i.d) random vector which is sampled from a M-dimensional Gaussian distribution $P_i(V^t \phi_i)$. Here, $\phi_i = (\rho_{i1}, \ldots, \rho_{iM}, m_{i1}, \ldots, m_{iM})$ is the parameter of the Gaussian distribution. Following the assumptions, we can derive that for a given region Ω_i, the probability density function (PDF) of V is

$$F(V(x)|\Omega_i, \varphi_i|) = \prod_{j=1}^{M} \frac{1}{\sqrt{2\pi}\rho_{ij}} e^{-\frac{\left(G_j v(x) - m_{ij}\right)^2}{2\rho_{ij}^2}}. \tag{5}$$

Because all of the samples are i.i.d, then, for the region Ω, the joint PDF (the likelihood) of V is

$$F\left(V(x)|\{\Omega_i\}_{i=1:N}, \{\varphi_i\}_{i=1:N}\right) = \prod_{i=1}^{N} \prod_{j=1}^{M} \frac{1}{\sqrt{2\pi}\rho_{ij}} e^{-\frac{\left(G_j v(x) - m_{ij}\right)^2}{2\rho_{ij}^2}}. \tag{6}$$