SUBSPACE BASED ACTIVE CONTOURS WITH A JOINT DISTRIBUTION METRIC FOR SEMI-SUPERVISED NATURAL IMAGE SEGMENTATION

Shu-Juan Peng[*], *Xin Liu*[⋄] *and Yiu-ming Cheung*[⋄]

[*] Department of Computer Science and Technology, Huaqiao University, Xiamen, 361021, China
[⋄] Department of Computer Science, Hong Kong Baptist University, Hong Kong SAR, China
Email: pshujuan@hqu.edu.cn, {xliu,ymc}@comp.hkbu.edu.hk.

ABSTRACT

In this paper, we present an efficient active contour with a joint distribution metric for semi-supervised natural image segmentation. Firstly, we project an RGB image into two-dimensional subspace and draw a polygon curve around the Region of Interest (ROI) as the initial evolving curve. Then, we model the regional statistics in terms of joint probability distributions and propose an effective distribution metric to regularize the active contours for evolution. Subsequently, we convert the resultant zero level set function into binary pattern and find all the 8-connected regions. Finally, the largest region is selected as the desired ROI and smoothed with a circular averaging filter so that the corresponding final segmentation result can be obtained. Meanwhile, the proposed approach also features fast convergence and easy implementation in comparison with the traditional methods, which need a laborious process of re-initializing the zero level set in terms of a sign distance function (SDF) periodically. The experiments show the promising results.

Index Terms— Subspace, active contours, joint distribution metric, semi-supervised, natural image segmentation.

1. INTRODUCTION

Natural image segmentation is to find the region of interest (ROI) through partitioning a natural image into disjoint regions. In the past, it has been received wide attention in the fields of computer vision and pattern recognition because of its attractable applications in image retrieval, scene classification, object tracking, and so forth. Nevertheless, it is still a challenging topic because the natural images are almost always composed of both non-significant edges, inhomogeneous intensity distributions, and complex appearances.

The active contour, one of the most successful models, based on level set theory, has been extensively studied and successfully utilized for image segmentation. It aims at driving an initial contour to evolve toward the ROI boundaries with an arbitrary topology. Roughly, the active contour can be classified into two branches: the edge-based models and the region-based models. The edge-based models mainly utilize the low level spatial cues such as edge information via gradient constraint to stop a contour on the boundaries of the desired objects [1], but which is prone to local minimum and susceptive to the image noise. By contrast, the region-based models basically adopt image statistical characteristics to drive the motion of the active contour for extracting the ROI, which has often shown a better segmentation result than the edge-based methods if the object incorporates weak boundaries. Nevertheless, intensity inhomogeneity and complex appearance often emerge in real images in terms of different modalities. Vese and Chan [2] found an optimal approximation via a piecewise smooth function to model region property for segmentation. Li *et al.* [3] addressed a local binary fitting (LBF) energy with a kernel function to segment objects with intensity inhomogeneities by taking local image information into consideration. Instead of modeling the global image statistics with localized version, Lankton *et al.* [4] presented a localized active contour and evolve the curve via a localized energy function. Nevertheless, most of active contour based techniques often focus on gray-scale pattern. These methods have shown the promising segmentation performance in their applications, but may not work well on natural images. It is well-known that color information is an important distinction features for image analysis. Although the above energy functions or frameworks can be readily extended to the vector-valued case, the simply averaging of these values may not generate a good segmentation result due to its limited capability in segmenting the natural images.

Recently, supervised or semi-supervised interactive algorithms have been successfully applied to natural image segmentation [5, 6]. Although these type of methods need to get some user-specified foreground and background pixels in advance, it has a high accuracy of performing segmentation task. In this paper, we shall focus on semi-supervised natural image segmentation using active contours with limited assistance. Firstly, we draw a polygon curve around the ROI,

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and then utilize a subspace based joint distribution metric to regularize the active contours. Then, we select the largest 8-connected region and smooth it with a circular averaging filter such that the final segmentation result is obtained. We evaluate the proposed segmentation approach on the Berkeley Data set[1]. The experiments have shown the promising results.

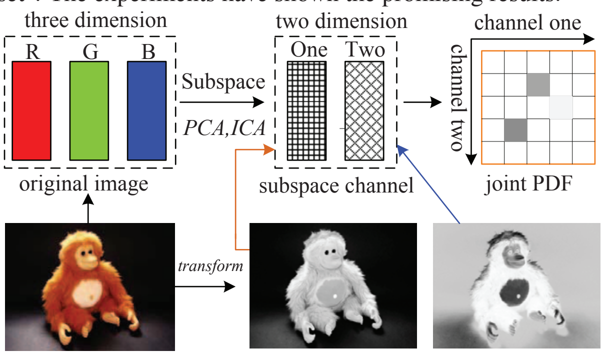

Fig. 1. The subspace based joint probability density function.

2. ACTIVE CONTOURS WITH SUBSPACE BASED JOINT DISTRIBUTION METRIC

The natural images are always stored with RGB patterns. The differences of the density distribution in each color channel are so similar that it is difficult to utilize one single channel to process the ROIs. As shown in Fig. 1, every point in RGB channel has three color attributes, which can be transformed into two-dimensional case inspired by the subspace theories, *e.g.,* PCA and ICA. The obtained two dimension channels often maintain the significant information for differentiation.

Let I denote an input image defined on the domain Ω. C represents a closed curve of a zero level set ϕ, *i.e.*,

$$\begin{cases} C = \{x \in \Omega : \ \phi(x) = 0\}, \\ interior\ (C) = \{x \in \Omega : \ \phi(x) < 0\}, \\ exterior\ (C) = \{x \in \Omega : \ \phi(x) > 0\}. \end{cases} \quad (1)$$

The basic idea of the active contour is to evolve the curve C so that the interior part will match the ROI and exterior part will represent the background. In general, a smoothed Heaviside function $H_\varepsilon(\phi)$ is always utilized to represent the interior area of the curve $\mathcal{C}$ while a smoothed Dirac function δ_ε is utilized to specify the area adjacent to $\mathcal{C}$, *i.e.*,

$$\begin{cases} H_\varepsilon(x) = \frac{1}{2}(1 + \frac{2}{\pi}\arctan(\frac{x}{\varepsilon}) \\ \delta_\varepsilon(x) = \frac{1}{\pi} \cdot \frac{\varepsilon}{\varepsilon^2 + x^2}. \end{cases} \quad (2)$$

Similarly, $(1 - H_\varepsilon(\phi))$ represents the exterior area of $\mathcal{C}$.

According to the work in [7], the general evolution process can be performed by minimizing a pre-specified evolution energy function according to the following flow:

$$\frac{\partial \phi}{\partial t} = E_{evolve} \cdot (div(\frac{\nabla \phi}{|\nabla \phi|}) + \alpha) + \nabla E_{evolve} \cdot \nabla \phi \quad (3)$$

[1]http://www.eecs.berkeley.edu/Research/Projects/CS/vision/bsds/

where the parameter α controls the contour shrinking or expanding. As a matter of fact, the function E_{evolve} mainly modulates the signs of the pressure forces between the interior region and exterior region such that the contour expands inside the object or shrinks outside the object.

The traditional region-based active contours always utilize the mean intensity to regularize the curve evolving. Subsequently, the objects of interest and background in natural images may always incorporate intensity inhomogeneities or complex appearances. Simply utilizing or averaging the mean intensity within the global or local region cannot successfully extract the ROIs. Hence, the distribution metric is employed [7]. Let T represent the transformed vector-valued image with two subspace channels, *i.e.,* $T = (T_1, T_2)$. $P_{in}((z_1, z_2))$ and $P_{out}((z_1, z_2))$ are the smoothed joint probability distribution functions (PDF) defined on the random variable z_1, z_2 inside and outside the curve $\mathcal{C}$, respectively, *i.e.,*

$$\begin{cases} P_{in}((z_1, z_2), \phi) = \frac{K_\sigma * \int_\Omega \mathcal{K}((z_1,z_2)-(T_1(x),T_2(x)))\cdot H(\phi)dx}{\int_\Omega H(\phi)dx} \\ P_{out}((z_1, z_2), \phi) = \frac{K_\sigma * \int_\Omega \mathcal{K}((z_1,z_2)-(T_1(x),T_2(x)))\cdot(1-H(\phi))dx}{\int_\Omega (1-H(\phi))dx} \end{cases} \quad (4)$$

where K_σ is a two-dimensional Gaussian kernel with standard deviation σ for smoothness, $\mathcal{K}((z_1, z_2) - (T_1(x), T_2(x))$ is a specified Gaussian kernel for selecting joint densities. (z_1, z_2) is selected to be a group of intensity values.

As shown in [7], the popular Bhattacharyya distance can be efficiently utilized to measure the similarity between the PDFs, *i.e.,* $\mathcal{B} = \int_{\boldsymbol{z}} \sqrt{P_{in}(\boldsymbol{z})P_{out}(\boldsymbol{z})}d\boldsymbol{z}$. By substituting this value and its first variation into Eq. (3) such that it can evolve the curve C to match the boundary of ROIs. This distance can be extended to vector-valued case. However, it may not have a good performance by simply averaging the PDFs in all the channels for natural images. Meanwhile, the Bhattacharyya gradient flow needs to compute the deviation, which is somewhat complex in formulation and computation.

In general, the values of smoothed PDFs between the regions of the background and objects in grey-level case are the most different, but still have intersecting parts [8]. It is found that these values of intersecting parts always represent the boundary parts of ROIs. Inspired by the work addressed in [8], we transform the color natural images into subspace case and obtain two subspace channels. Subsequently, it is easy to obtain the joint PDF within these two channels. Similarly, the two-dimensional smoothed PDF surface also has intersecting parts as illustrated in Fig. 2(c) and Fig. 2(d), respectively. The intersecting parts always belong to the boundary part. In contrast, the values excluded the boundary parts obtained via the interior region (object) and exterior region (background) are always different. As the function E_{evolve} in level set evolution mainly modulates the signs of the pressure forces, we therefore take this significant information into account and propose a novelly joint distribution metric (JDM) acted on the interior region and exterior region, respectively,

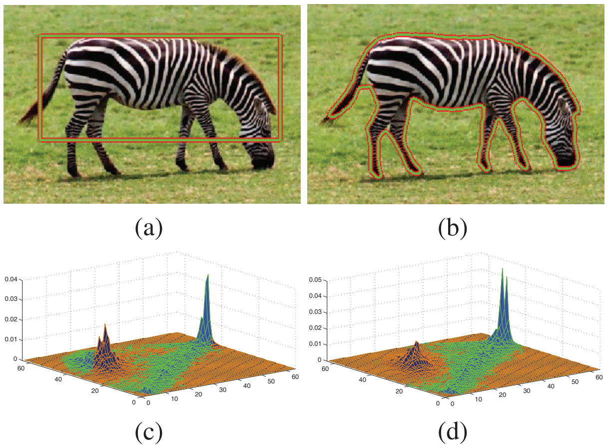

Fig. 2. (a) Color Zebra image with the initialized contour, and its corresponding ICA-based Joint PDF (c); (b) Segmentation result, and its corresponding ICA-based Joint PDF (d).

to regularize the active contours. Let $A_{in} = \int_{\Omega} H(\phi)dx$ and $A_{out} = \int_{\Omega}(1 - H(\phi)dx$ represent the area of inside and outside contour, individually. The proposed JDM is formulated:

$$JDM((T_1(x), T_2(x)) = \mathcal{K}((z_1, z_2) - (T_1(x), T_2(x)) \cdot (\frac{P_{out}((z_1, z_2), \phi)}{A_{\min}} - \frac{P_{in}((z_1, z_2), \phi)}{A_{\max}}) \quad (5)$$

where $A_{min} = min\{A_{in}, A_{out}\}$ and $A_{max} = max\{A_{in}, A_{out}\}$ are specially utilized to make a better distinction between the ROIs and background as the values of joint PDF of the interior region belonging to the boundary parts always hold a larger proportion than the background. In addition, according to the investigation in [9], the curvature-based term $div(\frac{\nabla\phi}{|\nabla\phi|})$ can be removed because the utilization of the statistical information modeling the regions has the ability to capture a larger range. Therefore, the proposed level set formulation can be reformulated as follows:

$$\frac{\partial\phi}{\partial t} = \delta_{\varepsilon}(\phi) \cdot (JDM((T_1(x), T_2(x))) \cdot \alpha \left|\nabla\phi\right|. \quad (6)$$

3. IMPLEMENTATION DETAILS

In classical active contours, the level set function is initialized to be a sign distance function (SDF). Such an operation often needs a number of iterations to reach zero level set, which may be quite time-consuming. Hence, following the idea proposed in [9] to achieve fast convergence and easy implementation, we firstly initialize the level set function to be the constants, which has different signs inside and outside the contour. Then, we utilize a Gaussian filter to regularize the level set function at each iteration. The main steps of the proposed algorithm are summarized as follows:

1. Transform RGB image I via PCA or ICA and select two subspace channel T, quantize the intensities into [1,266].

2. Manually draw a polygon around the ROI, and select the polygon curve as the initial evolving curve.

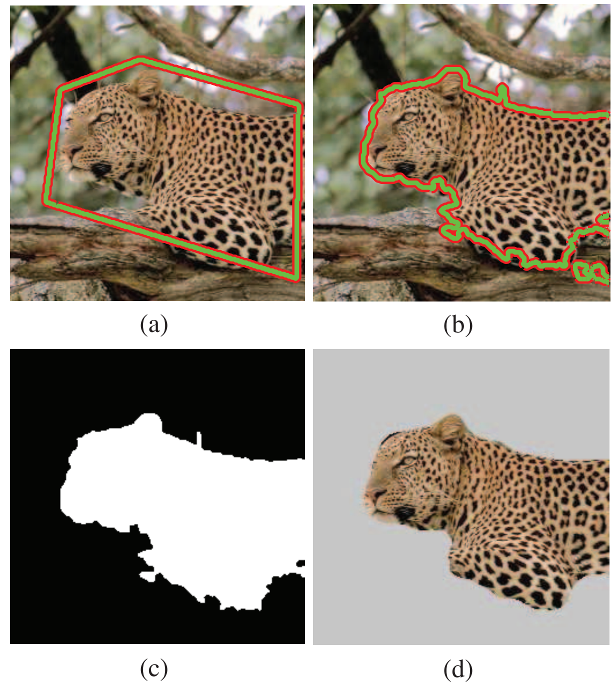

Fig. 3. (a) Leopard image with the initialized polygon; (b) Initial segmentation result via active contours; (c) Remove small 8-connect region and keep the largest one; (d) Final segmentation result.

3. Initialize the level set function ϕ as:

$$\phi(x) = \begin{cases} -\rho, & x \in \Omega_0 - \partial\Omega_0 \; (interior\ region) \\ 0, & x \in \partial\Omega_0 \; (boundary\ part) \\ \rho, & x \in \Omega - \partial\Omega_0 \; (exterior\ region) \end{cases} \quad (7)$$

where ρ is a constant, *e.g.*, $\rho = 1$ or 2.

4. Smooth the function $\phi(x)$ with a Gaussian filter, *i.e.*, $\phi = G_\sigma * \phi$, set $\varepsilon = \frac{\rho}{2}$ to obtain δ_ε via Eq. (2).

5. Compute $P_{in}((z_1, z_2), \phi)$ and $P_{out}(z_1, z_2), \phi)$ via Eq. (4), z_1 and z_2 are of the same bin numbers.

6. Evolve the curve through the function Eq. (6).

7. Let $\phi = \rho$ if $\phi > 0$; otherwise $\phi = -\rho$.

8. Regularize ϕ with a Gaussian filter, *i.e.*, $\phi = G_\sigma * \phi$.

9. Examine whether the evolution of the level set function has converged. If so, we obtain the initial segmentation result. Otherwise, goto Step 5.

10. Convert the resultant ϕ into the binary pattern and find all 8-connected regions. If the number of 8-connected region is larger than one, the largest 8-connected region is selected as the desired ROI.

11. Finally, by smoothing the selected ROI with a circular averaging filter, the segmentation result is obtained.

Note that, the manually selected polygon should contain some representative components of the ROI, which need not fully enclose the target ROI.

4. EXPERIMENTAL RESULT

In our experiments, we let $\rho = 2$, $\varepsilon = 1$, $\sigma = 1.5$. The value of α was selected according to the scale of different im-

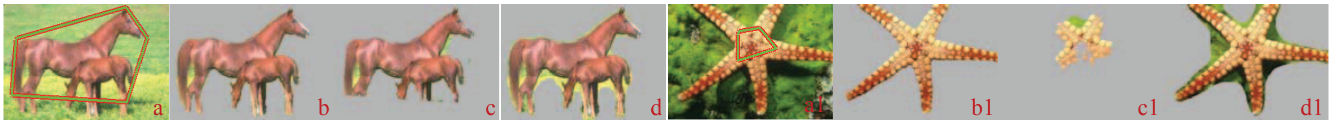

Fig. 4. The corresponding segmentation result. (a)&(a1): original natural image with initial polygon curve, (b)& (b1): results obtained by the proposed algorithm. (c)& (c1): results obtained by [7] in grey-level case, and (d)& (d1): results obtained by [8].

ages. Please refer to literature [9] for details. The intensity histograms with $z_1 = 1, \cdots, 256$ and $z_2 = 1, \cdots, 256$ bins were employed. The fastICA[2] associated with PCA analysis was utilized for subspace channel selection. We set the subspace dimensionality at 2.

The popular Zebra image has been widely utilized in state-of-the-art image segmentation algorithms. In grey level case, it has different density distribution of its own part while the grass background incorporates intensity inhomogeneities. In color version, as shown in Fig. 2, the color Zebra image has been successfully segmented using the proposed algorithm. The Leopard image, as shown in Fig. 3, has more complex and similar background, *e.g.,* tree branches. The active contours regularized with the subspace based joint distribution metric can extract the majority part of the Leopard region. The proposed 8-connected region searching method can successfully find the irrelevant yield small regions. The selected 8-connected region smoothed with a circular averaging filter holds the capability that the boundary of rough fractions can be reduced such that the promising segmentation result is obtained as shown in Fig. 3(d).

Also, we compared the proposed natural image segmentation approach with Sandhu *et al.* [7] in grey-level case and Michailovich *et al.* [8] in color space. Two examples of natural image segmentations are shown in Fig. 4. The densities of ROIs in these two images are inhomogeneous in its own region while being distinct from the backgrounds. It is difficult to generate the desired segmentation region when processing in grey-level case. The method in [7] handling these two natural images in grey-level case cannot well extract the whole part of the ROIs (some small fractions of ROI in Fig. 4(a) are missed while the large parts in Fig. 4(a1) are not included). Meanwhile, the method in [8] fails to get precise object boundary in color case. In contrast, it can be observed that the proposed approach can well segment the desired ROIs. Differing from the interactive methods in [5, 6], the proposed method need not specify some foreground and background pixels carefully but just utilize a polygon instead. In particular, as shown in Fig. 4(a1), we only need to draw a small polygon curve centered at the ROI and the proposed method can well segment the whole objects.

Furthermore, the proposed method integrates the superiorities of the method [9] in terms of regularizing the active contours with a Gaussian filter and avoids the usual drawback of computational complexity in the level set approach that consists of initializing the active contour in an SDF and re-initializing it periodically during the evolution. Therefore, the proposed approach has the advantages of computationally efficient, fast convergence and easy implementation, which only needs to take a few iterations and less computing time to obtain the desired results. From the experimental results, our method is feasible and effective.

5. CONCLUSION

In this paper, we have presented an efficient subspace based active contours with a joint distribution metric for natural image segmentation. The proposed method only needs to draw a polygon over the target object such that the proposed distribution metric can well regularize the active contour driving to the object boundary. The proposed 8-connected region selecting method associated with the circular averaging filter can make the final segmentation result better. The experiments have shown the promising result.

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