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Adaptive shape prior in graph cut image segmentation

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ABSTRACT

This paper presents a novel method to apply shape priors adaptively in graph cut image segmentation. By incorporating shape priors adaptively, we provide a flexible way to impose the shape priors selectively at pixels where image labels are difficult to determine during the graph cut segmentation. This is in contrast to the use of shape priors indiscriminatively at all pixels in existing image segmentation approaches, which may fail if the parameters for the shape prior term are not chosen appropriately. We integrate the proposed method in two existing graph cut image segmentation algorithms, one with shape template and the other with the star shape prior. To determine the need for a shape prior at each pixel, our experiments make use of either the original image or an enhanced version of the original image by smoothing. Experimental results in multiple application domains demonstrate the generality and superior performance of our adaptive shape prior method.

1. Introduction

Image segmentation has always been an important and challenging task in computer vision. Since Boykov and Jolly [1] introduced the application of the graph cut algorithm into image segmentation, graph cut has become one of the leading approaches in image segmentation in the last decade, because it not only allows one to incorporate user interaction, but also is an efficient and globally optimal algorithm.

More recently, in order to handle noisy images or images with object occlusions effectively, new methods have been developed to exploit shape priors. Freedman and Zhang proposed to incorporate shape priors by matching the segmented curve with a shape template [2]. Veksler showed how to implement a shape prior for objects defined as star shaped [3]. Das et al. presented a similar idea to incorporate shape priors for shapes defined as compact [4]. In addition, some research activities focus on one or two particular types of objects with particular shapes [5,6], some on incorporating multiple shape priors into one image [7], and yet some on shape representation and general shape constraints [8,9].

One of the problematic issues of the graph cut framework is the selection of weights on the various terms in the energy function. These weights are usually tuned beforehand by the developer of the algorithm to achieve the best result for a certain type of images [10]. For example, Peng and Veksler [10] designed a parameter selection method by measuring segmentation quality based on different features of the segmentation. They ran graph cut for different parameter values and chose the parameters which produce segmentation of the highest quality. However, their method only targets issues of selecting the parameters between the data term and the boundary term in the energy function, while setting a constant weight on the shape prior. For images corrupted by significant noise and intensity inhomogeneities, the needs for a shape prior at different pixels are different in general. Therefore, setting a constant weight on the shape prior term for all pixels may not be appropriate. As an example, columns (b) to (d) in Figs. 1 and 2 show examples where different parameter settings for the shape prior can lead to very different segmentation results.

To solve the issue described above, we propose to impose shape constraints selectively, by applying the shape prior adaptively in graph cut. To determine the need for the shape prior at each pixel, we derive a shape weight term based on image intensity. The intuition behind this is that if a pair of neighboring pixels has a small difference in appearance, there should be a higher weight for the shape constraint in the energy function to compensate for the weak or missing edge information. In this way our method gives flexibility in applying a shape prior, and helps obtain a segmentation result that matches better with the shape prior. As will be seen in our paper, this weight on the shape constraint can be easily calculated without much additional computational cost.

An adaptive graph cut idea has been proposed by Song et al. [11] where they proposed a framework for segmentation of brain tumors in MRI images within an iterative scheme. They incorporated a shape atlas of adaptive probabilistic priors into the graph cut energy function by combining it with the image intensity

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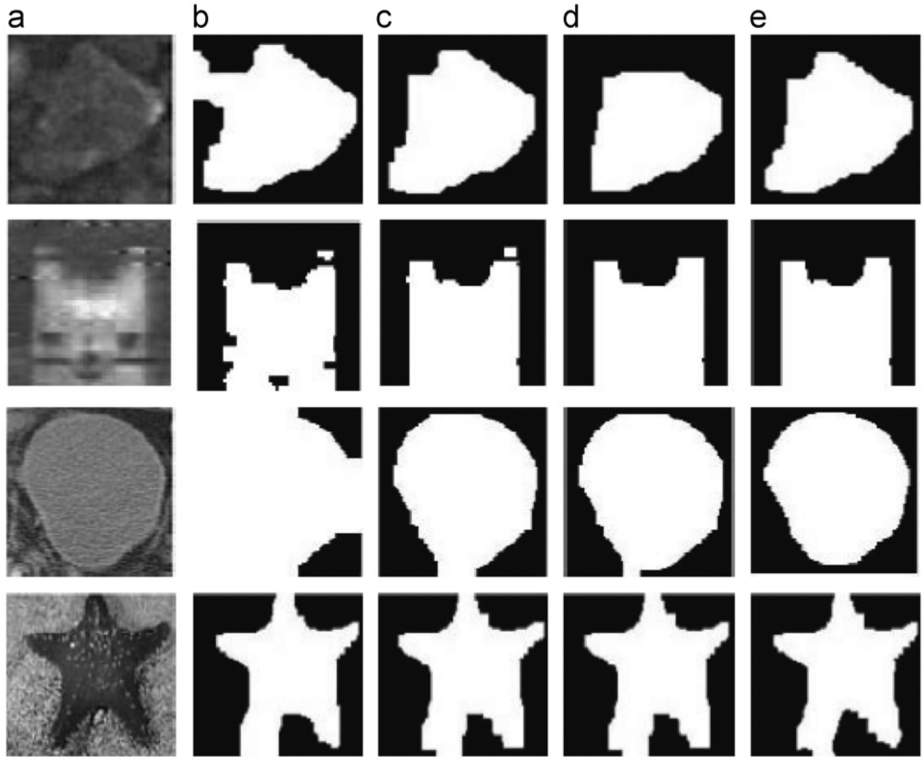

Fig. 1. Results from the shape template based method [2]. Column (a) shows the original images. Columns (b)–(d) show segmentation results from Freeman and Zhang's original shape template method with $\lambda = 0.2$, 0.5 and 0.8. Column (e) shows segmentation results from our adaptive shape prior applied to Freedman and Zhang's shape prior method. Column (e) uses smoothed images as the probability maps α.

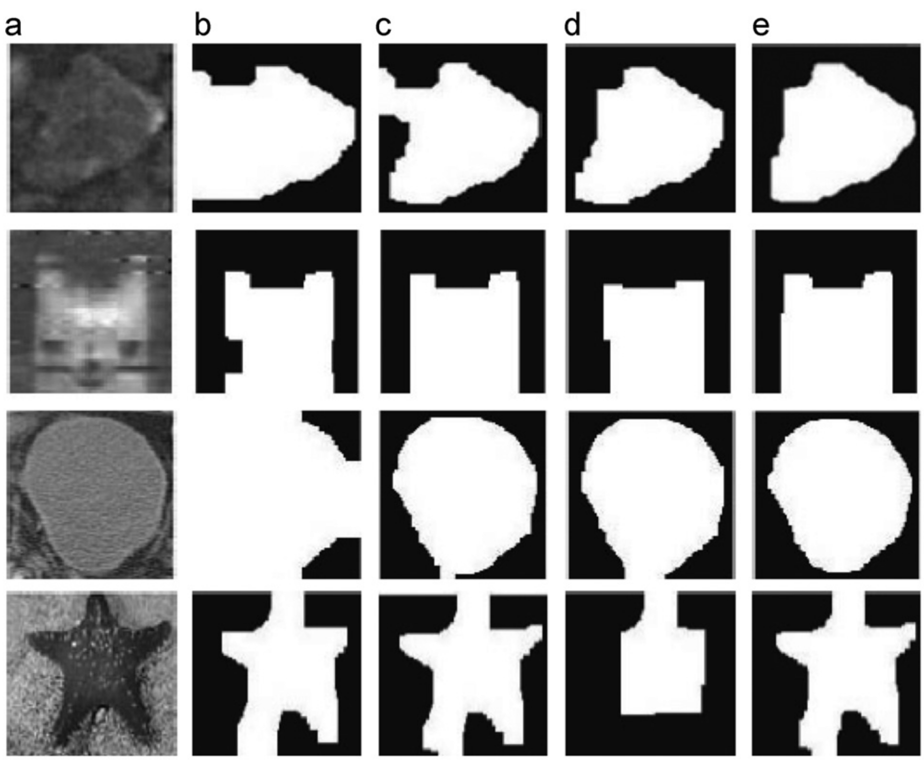

Fig. 2. Results from the star shape prior method [3]. Column (a) shows the original images. Columns (b)–(d) show segmentation results from the original star shape prior method with $\lambda = 0.2$, 0.5 and 0.8. Column (e) shows segmentation results from our adaptive shape prior applied to Veksler's star shape prior method. Column (e) uses smoothed images as the probability maps α.

distribution. However, the adaptive idea suggested in [11] works on the combined data term only, instead of on the pairwise terms. Furthermore, the performance of their method relies a lot on the accuracy of the atlas, and several parameters, such as the weight λ between the data and boundary terms, as well as the scale for calculating the neighborhood links.