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Integration of the saliency-based seed extraction and random walks for image segmentation

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ABSTRACT

In this paper, a novel automatic image segmentation method is proposed. To extract the foreground of the image automatically, we combine the region saliency based on entropy rate superpixel (RSBERS) with the affinity propagation clustering algorithm to get seeds in an unsupervised manner, and use random walks method to obtain the segmentation results. The RSBERS first applies entropy rate superpixel segmentation method to split the image into compact, homogeneous and similar-sized regions, and gets the saliency map by applying saliency estimation methods in each superpixel regions. Then, in each saliency region, we apply the affinity propagation clustering to extract the representative pixels and obtain the seeds. A relabeling strategy is presented to ensure the extracted seeds inside the expected object. Additionally, in order to enhance the effects of segmentation, a new feature descriptor is designed using the covariance matrices of coordinates, color and texture information. Experiments on publicly available data sets demonstrate the excellent segmentation performance of our proposed method.

1. Introduction

According to certain similar criteria of some low-level visual features, such as color, texture, shape etc., image segmentation refers to partition a single image into non-overlapping regions, and then extract the objects of interest under the complex background environment. It has been found, in a wide range of applications, to be not only a fundamental problem but also the key problem in the research of image analysis, pattern recognition [1], computer vision, medical image processing [2], and even image understanding. It is precisely because of its important academic value and great potential for practical application, a lot of research works in this area have been developed in the last 2 decades. According to the fact whether requiring the user's participation in the segmentation process, existing image segmentation methods can be generally divided into automatic and interactive methods.

Automatic approaches do not require any user participation and prior information about the image. Given an image, these methods can obtain segmentation results automatically. Shi and Malik [3] defined image segmentation as a graph partitioning problem and developed normalized cuts criteria to partition the graph. In [4,5] level set framework is developed for image segmentation, which is based on boundary contours evolution. Mean shift [6] method is still considered as the most important algorithm for color image segmentation. Recently, an unsupervised image segmentation algorithm was presented in [7]. This method modeled each phase using multiple piecewise constants, and minimized the new energy model with graph cuts optimization method. Ugarriza et al. [8] adopted the dynamic region growing and multi-resolution merging technique for automatic natural image segmentation. Browning et al. [5] proposed the ViSTARS neural model which uses motion information to segment objects in response to video inputs from real and virtual environments. Although those approaches can automatically partition image into some separate regions, due to the lack of prior information about the objects in an image, it is hard to provide the ideal segmentation results about real-world natural scene images.

Interactive image segmentation methods incorporate minimal user interactive into the segmentation process. Due to its good segmentation performance, interactive methods have attracted significant attentions in recent years. A representative segmentation method that

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belongs to the boundary-based interactive segmentation method has been proposed by Mortensen and Barrett [9]. This method requires the user to control the mouse along the boundary of the object and place several marks, and the Dijkstra's shortest path algorithm is then used to finish the segmentation of the object. Another example of interactive segmentation method is the active contour method [10], which is able to capture salient image contour. In this method, an initial contour is placed near the boundary of the object of interest and the contour is evolved to catch the object boundary.

The third method is seed-based interactive segmentation method. The typical methods are the graph cuts based methods [11–15] and random walks algorithm [16]. The user is asked to provide an initial labeling of some pixels as belonging to the desired object or background (known as seeds), and then the algorithm completes the labeling for all pixels in the image based on the seed clues. Here image segmentation is treated as a graph optimization problem and the image is represented as a weighted graph where each vertex of this graph corresponds to a pixel or region and each edge with weight indicates the similarity relationship between neighbor pixels. Boykov and Jolly [11] proposed the interactive graph cuts method for gray-scale image segmentation method, where the probability distributions of the image foreground and background are described with histograms of gray values, and then the min-cut algorithm is adopted to find the globally optimal segmentation. Similarly in [12] the authors proposed a coarse-to-fine interactive foreground extracted method named Lazy Snapping, where the multiple average color of these seed regions is used to build the distributions of the foreground and background. Rother et al. proposes GrabCut [13] method, where the Gaussian mixture model is used to model the foreground and background and the iterative process between model estimation and parameter learning based on graph cuts is used to optimize the segmentation results until convergence. Tao et al. [17,18] extended the interactive binary segmentation to multiphase image method based on variational model and graph cuts optimization. Hu et al. [19] presented a fast and accurate semiautomatic contour delineation method. It uses a conditional random field graphical model to define the energy minimization function for obtaining an optimal segmentation, and applies a graph partition algorithm to efficiently solve the energy minimization function. The random walks algorithm [16] treats the edge weights as probabilities of a particle at one node traveling to a neighboring node. Given seeds, the probability that a particle at any unlabeled pixel first travels to the foreground or background seeds are used as the basis for image segmentation [16,20].

These interactive methods introduced above can achieve impressively accurate results. However, the manual interactions are time-consuming and often infeasible in many practical applications. These shortcomings limit the applications of the interactive methods for image segmentation.

The segmentation quality of current interactive tools depends heavily on the seeds extraction. To address the inherent problems of the interactive image segmentation methods, some researchers have been tried to develop full-automatic segmentation approaches by integrating the saliency detection technologies. Firstly the object seeds are extracted by some saliency detection methods, and then one interactive segmentation method is used to finish the final object segmentation. There are many methods to extract saliency regions from an image based on human visual theory [21–31]. Fu et al. [32] put forward an approach named Saliency cuts, which designs a multi-resolution framework to provide the object segmentation automatically. In [33], an iterative self-adaptive framework is developed and the min-cut algorithm is used to segment the salient objects. Cheng et al. [31] automatically initialized GrabCut by binarizing the saliency map, and then iteratively applied GrabCut to improve the segmentation results.

Recently the random walks segmentation has been introduced to interactive image segmentation and shown to have desirable theoretical properties and perform well in many practical applications [16]. Its major advantage is that the solution for random walk energy function is exact and unique minimum. Therefore, this method can likely achieve better performance especially in the presence of weak boundaries and noise. However, due to the fact that it lacks a global feature distribution model, the random walks method is very sensitive to positions and quantities of foreground and background seeds. It is known that the positions of the comprehensive and uniform seeds would lead to accurate segmentation results and reduce or even eliminate the user interactions. However, the inaccurate selection of seeds usually results in inaccurate region labeling results so that more user interactions are required to extract the object of interest accurately. An example of this inherent problem of random walks is shown in Fig. 1, images with the superimposed seeds are shown in the first row, and the corresponding segmentation is displayed in the second row. As shown in columns 1–4 of Fig. 1, we can find that the segmentation results vary significantly from each other although the foreground and background seeds are all accurately marked. Comparatively, the position of comprehensive and uniform seeds position leads to a more pleasant segmentation result as shown in the last column of Fig. 1.

In this paper, we propose an automatic segmentation method using the random walks framework. In order to extract seeds with sufficient and accurate information automatically, this paper proposes an efficient seeds extraction method by integrating the

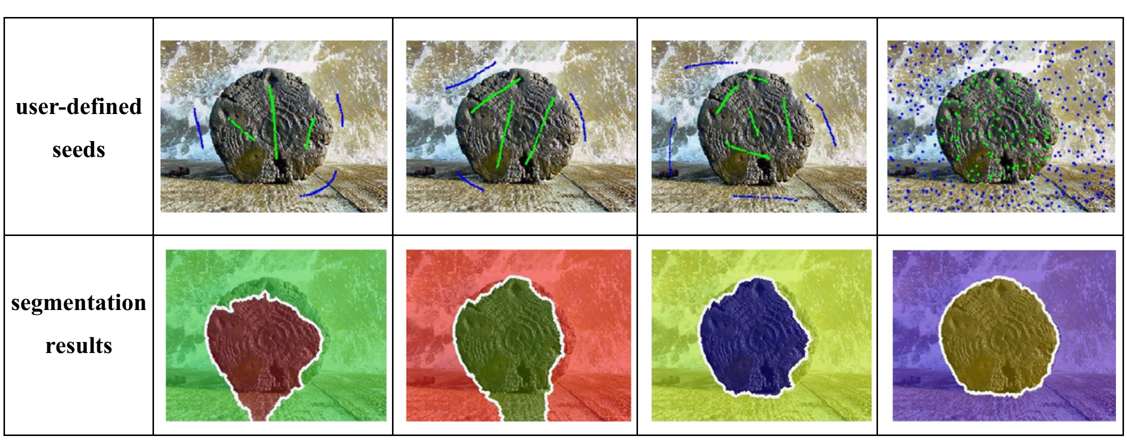

Fig. 1. Dependency on the seeds of random walks algorithm. The first row shows the original images (#0_3_3524 from the saliency object database Free 1000) with superimposed user-specified seeds (green lines (points) for the foreground and blue lines (points) for background) and the second row displays the segmentation results obtained from the corresponding seeds. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)