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Image Segmentation Based on Fast Normalized Cut

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Abstract: In this paper, we propose a fast image segmentation method based on normalized cut. This method apply simple linear iterative clustering super-pixel algorithm to obtain super-pixel regions, and then use affinity propagation clustering to extract the representative pixels in each super-pixel regions, Finally, we apply normalized cut to obtain segmentation results. At the end of the paper, Numerical experiments are presented to demonstrate the effectiveness of our proposed method.

Keywords: Clustering, image segmentation, super-pixel, normalized cut.

1. INTRODUCION

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 homogeneous regions, and then extract the objects of interest under the complex background environment. It has been found not only a fundamental problem but also the key problem in the field of medical image processing [1], pattern recognition [2], computer vision, and even image understanding.

During the past decades, a rich amount of literature on image segmentation has been published. Graph-based methods [3-6] first map the image elements onto a graph, and then solve the segmentation problem in a spatially discrete space by the efficient tools from graph theory. Due to its good segmentation performance, graph-based methods have attracted significant attentions in recent years. One well-known method is proposed by Shi *et al.* [6] in terms of normalized cut (NCUT). However, in most applications, normalized cut method using image pixels for segmentation. The number of pixels in an image is very large generally, so there are exponential numbers of possible partitions of the graph. As a result, it is computationally expensive to find the optimal partition. In order to improve the speed and the effects of the NCUT segmentation, the paper design a new fast segmentation algorithm based on normalized cut. Firstly the algorithm use simple linear iterative clustering super-pixel (SLIC) algorithm [7] to preprocess the image, as the image processed by SLIC algorithm will be divided into many regions, if we use some representative point instead of these regions, we can construct an undirected weighted graph to describe the relationship of these point, unlike the traditional NCUT algorithm used in image pixels, we directly applied NCUT algorithm to these areas for regional clustering to obtain segmentation results.

The remainder of this paper is organized as follows: Section 2 introduces our new fast segmentation method in detail. In Section 3, a number of comparison experiments using the real natural scene images are given to demonstrate the superior performance of our proposed method, followed by a brief conclusion in Section 4.

2. FAST NORMALIZED CUT

In this section, a fast normalized cut segmentation method was proposed. Our proposed method consists of three stages. We first use simple linear iterative clustering super-pixel algorithm to divide the image into many regions, and then applied affinity propagation clustering method [8] to extract the representative pixels in each super-pixel regions. Finally, we apply Normalized cut to obtain segmentation results.

2.1. Normalized Cut Segmentation Method

The normalized cut method represents an image as a graph where vertices are image pixels and the edge weights represent the feature similarities between pixels. Then image segmentation becomes a graph partitioning problem. The idea is to partition the vertices of the graph into disjoint sets so that the total similarity between different sets is minimized. The NCUT cost function is defined as follows:

$$Ncut(A,B)=\frac{cut(A,B)}{assoc(A,V)}+\frac{cut(B,A)}{assoc(B,V)} \tag{1}$$

where $assoc(A,V)$, $assoc(B,V)$, $cut(A,B)$, and $cut(B,A)$ can be expressed as following,

$$assoc(A,V)=\sum_{u\in A,t\in V} w(u,t) \tag{2}$$

$$assoc(B,V)=\sum_{u\in B,t\in V} w(u,t) \tag{3}$$

$$cut(A,B)=\sum_{u\in A,t\in B} w(u,t) \tag{4}$$

$$cut(B,A)=\sum_{u\in B,t\in A} w(u,t) \tag{5}$$

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The $assoc(A,V)$ is the total connection from nodes in A to all nodes in the graph and $assoc(B,V)$ is similarly defined. Note that with this definition, the minimization of Eq. (1) can be formulated into a generalized eigenvalue problem, which has been well-studied in the field of spectral graph theory. However, Due to that NCUT method using image pixel for segmentation, there are exponential numbers of possible partitions of the graph. As a result, it is computationally expensive to find the optimal partition. In this paper, we propose a new fast normalized cut method for image segmentation, which can not only greatly improve the speed of the segmentation method; it can also provide accurate segmentation results.

2.2. Represent Pixels Extracting

Super-pixel is a convenient method to compute local image features. They can capture the redundancy of the image and greatly reduce the complexity of subsequent image processing tasks. There are many approaches to generate super-pixels [7, 9-11], each with its own advantage and drawbacks that may be better suited to particular application. For better pre-processing results, in this paper, we choose SLIC algorithm to divide image into super-pixel regions. SLIC algorithm performs a local clustering of pixels in 5-D space and these 5-D respectively are L, a, b values of CIELAB color space and pixel coordinates x, y.

After getting the super-pixels regions, we use affinity propagation clustering [3] to extract represent pixels in each super-pixels region. AP algorithm was recently proposed by Dueck and Frey. It has been proved to be more effective than the classical clustering methods, such as k-means, k-centers etc. AP algorithm considers all data points of randomly selected subset as candidate centers. Using this method, many of the poor solutions caused by unlucky initializations can be avoided. Also, the number of identified exemplars in AP algorithm is not required to pre-defined and influenced by the values of the input preferences.

Finally, we construct an undirected weighted graph to describe the relationship of these represent pixel point, unlike the traditional NCUT algorithm used in image pixels, we directly applied NCUT algorithm to these areas for regional clustering to obtain segmentation results. Our proposed method can provide excellent segmentation results, and favors satisfactory segmentation speed.

3. EXPERIMENTS

In our experiments, we provide a number of real natural scene images for comparison, and these images are all from the saliency object database Free 1000 [12]. Additionally, to visualize the segmentation results more intuitively, we color the foreground and background with a different translucent color randomly. Before comparison experiments, we first give some parameters which we used in our proposed method. In the SLIC super-pixels algorithm, we can set 10 iterations for all images, and the number of super-pixels is set to 400 in all experiments. When implementing the AP algorithm, we set the input preferences to be the median of the input similarities.

All these experiments are performed on a notebook which is equipped with equipped with a 2.40 GHz Intel(R) Core(TM) i3 CPU and 4GB RAM. The whole system is implemented in MATLAB using OPENCV 1.0 library. Some of the most time consuming operations were implemented in C++ and interfaced with MATLAB through mex-files. Some

Fig. (1). Segmentation results, the images come from the saliency object database Free 1000: original images.

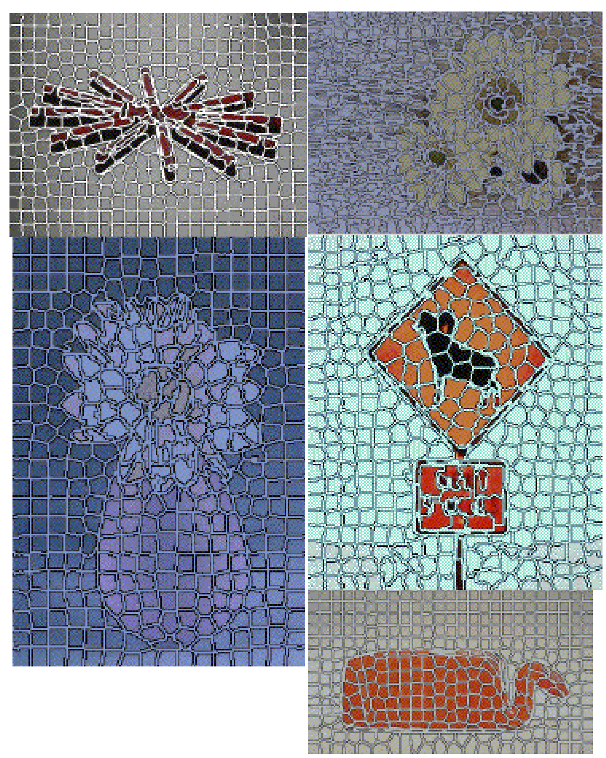

Fig. (2). Segmentation results, the images come from the saliency object database Free 1000: results of SLIC algorithm.

Fig. (3). Segmentation results, the images come from the saliency object database Free 1000: segmentation results of our proposed method.

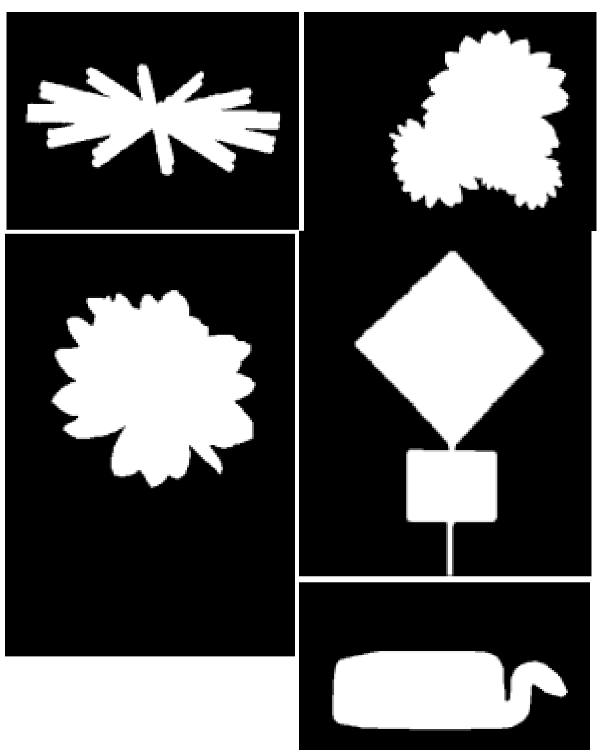

Fig. (4). Segmentation results, the images come from the saliency object database Free 1000: ground truth.

popular implementations were used the online available C++ or MATLAB code, such as SLIC method, affinity propagation clustering etc.

Figs. (**1-4**) show the excellent performance of our proposed method. Some testing images from the saliency object database Free 1000 are shown in Fig. (**1**). The Fig. (**2**) shows the results of SLIC algorithm. The segmentation results of our proposed algorithm are displayed in Fig. (**3**). Finally, the ground truths are shown in Fig. (**4**). From the comparisons of segmentation results, we can find that our proposed method can obtain satisfied segmentation results, and are close to the actual saliency objects (ground truths). Additionally, we also test the average running time of the proposed segmentation method. The results show that our proposed method can greatly improve the speed of segmentation.

CONCLUSION

In this paper, a new fast image segmentation approach is proposed. We first use simple linear iterative clustering super-pixel (SLIC) algorithm to divide the image into many super-pixel regions. After the preprocessing stage, the image, we apply the powerful affinity propagation clustering algorithm to each super-pixels region to get representative pixels. Finally, we directly applied NCUT algorithm to these areas for regional clustering to obtain segmentation results. At last, the comparison experiments demonstrate that our proposed method can obtain satisfactory segmentation results.

CONFLICT OF INTEREST

The author confirms that this article content has no conflict of interest.

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