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A Novel Image Segmentation Algorithm Based on Graph Cut Optimization Problem

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Abstract

Image segmentation, a fundamental task in computer vision, has been widely used in recent years in many fields. Dealing with the graph cut optimization problem obtains the image segmentation results. In this study, a novel algorithm with weighted graphs was constructed to solve the image segmentation problem through minimization of an energy function. A binary vector of the segmentation label was defined to describe both the foreground and the background of an image. To demonstrate the effectiveness of our proposed method, four various types of images were used to construct a series of experiments. Experimental results indicate that compared with other methods, the proposed algorithm can effectively promote the quality of image segmentation under three performance evaluation metrics, namely, misclassification error rate, rate of the number of background pixels, and the ratio of the number of wrongly classified foreground pixels.

Keywords: *Image Segmentation, Graph Cut, Energy function, Pixel*

1. Introduction

Image engineering is a rich research area that has been explored for many years [1]. Recently, researchers have classified image engineering into three domains, namely, image processing, image analysis, and image comprehension. Generally, image segmentation, which has been widely used in many different applications, is a key issue in the field of image processing. Image segmentation refers to the division of an image into several separate regions to represent various types of objects [2, 3].

Image processing specifically aims to implement the pattern recognition process, and image segmentation is a basic work in pattern recognition and computer vision. Image segmentation separates an image into several regions and then provides descriptions to these regions [4]. Using certain similar criteria of low-level visual features, such as color, texture, and shape, image segmentation is defined as the conversion of a digital image to several non-overlapping regions, which result in objects in images [5, 6].

Unfortunately, the visual contents of the images are characterized by diversity, complexity, and randomness; an in-depth understanding of the internal vision mechanism of people also remains lacking [7]. To the best of our knowledge, no mature segmentation approach exists to satisfy all the requirements for application environments.

Because of the lack of prior information about objects in an image, providing accurate image segmentation results is difficult with the use of existing methods. The development of an effective and highly accurate segmentation approach is therefore important.

2. State of the Art

Image segmentation is a high-level application that has been widely used in many fields, such as remote communication, military, remote sensing, meteorology, image processing, and intelligent transportation, to name a few. In this section, we discuss related works about image segmentation.

Wang et al. presented a robust and efficient approach to segment images with limited and intuitive user interaction; the proposed algorithm integrated geodesic distance information with the flexibility of level set methods in energy minimization, which depends on complementary strengths [8].

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Han et al. proposed a new model to deal with the image segmentation problem. This model was constructed through analysis of the characteristic of textile/fabric images. The main innovation in this work is its incorporation of a cartoon-and-texture decomposition process into the model, as well as its bias field function designed to estimate the deviation degree between the cartoon image and the piecewise constant approximation [9].

Miao et al. proposed a new algorithm to segment large topographic maps based on the ideas of fuzzy theory, randomized sampling, and multilevel image fusion. A large topographic map was randomly sampled first. Then, the optimal clustering centers were acquired with fuzzy c-means (FCM) clustering. Multilevel image fusion was developed to fuse the segmented images into the final segmentation maps [10].

To enhance the quality of image segmentation, Yu et al. proposed a method to construct a generalized fuzzy complement; the authors also developed a generalized fuzzy complement operator, which has a good property for parameter optimization in real applications [10].

Aside from the aforementioned works, other methods have been used for image segmentation, such as incorporating adaptive local information into fuzzy clustering [12], arbitrary noise models via solution of minimal surface problems [13], clustering technique optimized by cuckoo search [14], modified Gaussian mixture models incorporating local spatial information [15], conditional random field learning with convolutional neural network features [16], dynamic incorporation of wavelet filter in FCM [17,18], proliferation index evaluation [19], and fuzzy active contour model with kernel metric .

3. Methodology for Image Segmentation Based on Graph Cut Optimization

From the above analysis, we can see that image segmentation is a fundamental task in computer vision. In this section, we discuss the image segmentation problem, and some examples of image segmentation are described as follows.

Figure 1. Examples of image segmentation.

Suppose that R means the whole regions in an image, and then segmentation results are represented by separating R to several non-overlapping subsets, that is, $R_1, R_2, \cdots, R_N$, and the following equations should be satisfied.

$$R = \bigcup_{i=1}^{N} R_i \tag{1}$$

$$R_i \cap R_j = \varnothing, \; for \; i \neq j \tag{2}$$

Let $G = (V, E, W)$ be a graph, in which *V* refers to a set of vertices, *E* is a set of edges, and W denotes weights of graph edges. Graph cut of *G* is to divide the graph to two different disjoint sets, that is, $G = X \cup Y$. Afterwards, cost function of graph cut is defined as follows.

$$|C|_G = \sum_{m \in X, n \in Y} \varphi_{mn} \tag{3}$$

where parameter φ_{mn} refers to weight of edge E_{mn}. Assume that graph cut refers to a closed contour and discrete formula is exploited to calculate the contour length.

Graph cut optimization problem can be illustrated as follows.

$$Mincut\{C_1, C_2\} = \sum_{i=1}^{|C|} w_i \tag{4}$$

where $C = \{C_1, C_2\}$ refers to a partition and symbol w_i denotes the weight between the edges which connect the set C_1 and the set C_2. Furthermore, we suppose that $A = |A_1, A_2, \cdots, A_{|x|}|$ is a binary vector of segmentation label, and A_i denotes a label. Thus, A represents a segmentation scheme and it can describe both foreground and background of the image to be segmented. Hence, an energy function $E(A)$ for the image segmentation process is described as follows.

$$E(A) = \varphi R(A) + B(A) \tag{5}$$

where the following conditions should be satisfied.

1) $$R(A) = \sum_{x \in X} R_x(A_x) \tag{6}$$

2) $$B(A) = \sum_{\{x,y\} \in N} B_{\{x,y\}} \xi(A_x, A_y) \tag{7}$$

3) $$\xi(A_x, A_y) = \begin{cases} 0, & A_x = A_y \\ 1, & A_x \neq A_y \end{cases} \tag{8}$$

where symbol $R(A)$ denotes a regional properties representation, and parameter φ is used to define the weight of $R(A)$. Afterwards, weight between two various pixels is computed as follows.

$$\sigma(i, j, x, y) = 1 - \frac{1}{2} \cdot \left(P(i, j) + P(v_{ij} | F) - P(v_{xy} | F) \right) \tag{9}$$

where $P(i, j)$ means the edge probability of the pixel (i, j), and $P(v_{ij} | F)$ and $P(v_{xy} | F)$ refers to the probabilities which are belonged to pixel (i, j) and (x, y) respectively. Using the parameter $\sigma(i, j, x, y)$, the energy function can be computed by the following equation.

$$E(f) = \sum_{i,j \in \Omega} -\ln\left(P\left(v_{ij} \middle| f_{ij} \right) \right) + \sum \frac{\theta \cdot \rho(i, j, x, y) \cdot B(i, j, x, y) \cdot \xi(f_{ij} \neq f_{xy})}{D(v_{ij}, v_{xy})} \tag{10}$$

where θ is defined as a constant, $\rho(i, j, x, y)$ denotes the parameter which is used to describe the importance of neighborhood pixels (i, j) and (x, y). Then, image segmentation task is solved by optimize this energy function.

4. Experiment and Results Analysis

In order to test the effectiveness of our proposed algorithm, experiments are designed to conduct performance evaluation. Moreover, several image segmentation approaches are utilized, including: 1) Parzen-window based thresholding (PWT), 2) Double-threshold image binarization (DTIB), 3) Local gray level difference (LGLD), and 4) Normalized Cut (Ncut). In particular, dataset utilized in this experiment is the same as paper, and we choose four types infrared images in our experiment, that is, 1) Crow, 2) Eagle, 3) Airplane and 4) Sailboat. On the other hand, mis-classification error rate (ME), rate of number of background pixels (FPR), and ratio of number of wrongly classified foreground pixels (FNR) are exploited as performance evaluation criteria

Mis-classification error rate (ME) is defined as follows.

$$ME = 1 - \frac{|B_T \cap B_S| + |F_T \cap F_S|}{|B_T| + |F_T|} \tag{11}$$

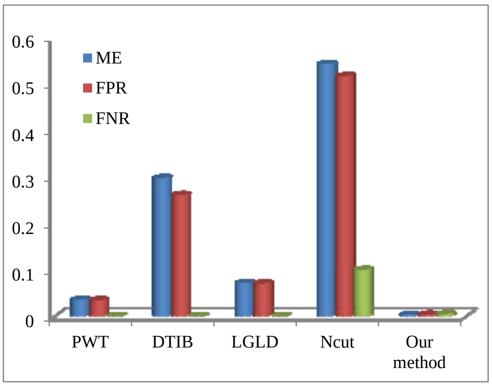
where B_T and F_T denote background and foreground for the ground truth image, moreover, B_S and F_S refer to background and foreground in segmentation results. Furthermore, lower value of ME metric demonstrates higher quality of segmentation results.

FPR represents the ratio of number of background pixels that mis-classified to the total number of background pixels, moreover, FNR denotes the ratio of number of wrongly classified foreground pixels to the total number of foreground pixels.

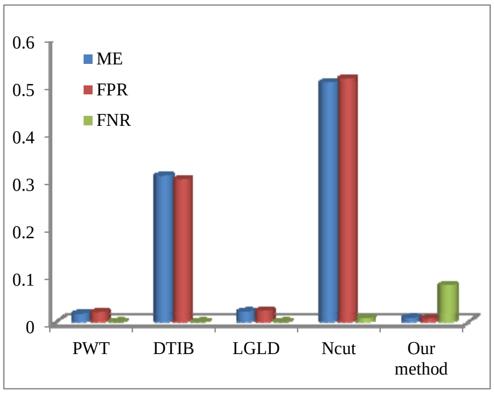
$$FPR = \frac{|B_T \cap F_S|}{|B_T|} \tag{12}$$

$$FNR = \frac{|F_T \cap B_S|}{|F_T|} \tag{13}$$

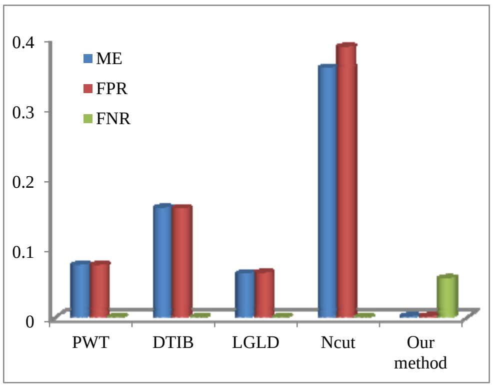
Afterwards, experimental results for the above three performance evaluation metrics with different methods are provided as follows.



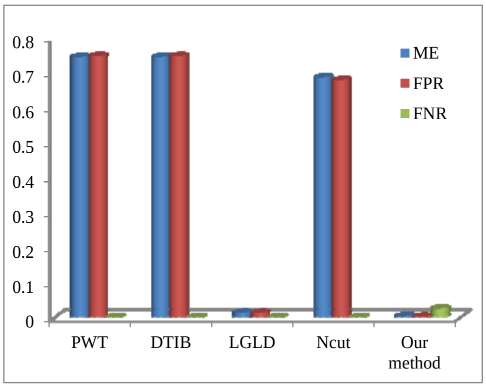
(a) Crow



(b) Eagle



(c) Airplane



(d) Sailboat

Figure 2. Experimental results for different image type

Integrating all the above experimental results, we calculate the average performance evaluation results from Figure 2 to Figure 5 as follows.

Table 1. Overall experimental results for all the four image types

	PWT	DTIB	LGLD	Ncut	Our method
ME	0.218	0.374	0.041	0.519	0.004
FPR	0.219	0.366	0.041	0.515	0.003
FNR	0	0	0	0.025	0.040

It can be seen from the above experimental results that our proposed graph cut based image segmentation algorithm is able to effectively segment images with high accuracy. The reasons lie in that 1) the graph model is able to describe relationships between different image pixels and then converts the image segment problem to graph cut optimization, and 2) graph cut optimization has the ability to deeply mine internal correlations between various graph nodes.

5. Conclusion

In this study, we presented a novel graph-cut-based image segmentation approach by converting the image segmentation problem to a graph-cut optimization problem. Inspired by the facts that an image can be separated into several regions, and image segmentation results are regarded as several non-overlapping regions, we convert the image segmentation task into a graph cut optimization problem. The main innovations of this study are its development of a binary vector of the segmentation label, which can describe both the foreground and the background of an image, as well as the segmentation of an image via minimization of an energy function. Particularly, the energy function is solved by estimation of the importance between neighbor pixels. To evaluate the performance of the proposed algorithm, ME, FPR, and FNR were used as the performance evaluation criteria. Four types of images were utilized to construct a data set, namely, the crow, eagle, airplane, and sailboat data sets. Finally, the experimental results show that our proposed algorithm can effectively produce accurate image segmentation results.

In the future, we will extend our work in the following aspects: 1) we will attempt to utilize the hierarchical graph cut algorithm in the image segmentation task, 2) we will introduce other optimization technologies to segment images (e.g., particle swarm optimization), and 3) we will test the performance of our proposed method by using other data sets.

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