Object Recognition Algorithm Utilizing Graph Cuts Based Image Segmentation

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***Abstract*—This paper concentrates on designing an object recognition algorithm utilizing image segmentation. The main innovations of this paper lie in that we convert the image segmentation problem into graph cut problem, and then the graph cut results can be obtained by calculating the probability of intensity for a given pixel which is belonged to the object and the background intensity. After the graph cut process, the pixels in a same component are similar, and the pixels in different components are dissimilar. To detect the objects in the test image, the visual similarity between the segments of the testing images and the object types deduced from the training images is estimated. Finally, a series of experiments are conducted to make performance evaluation. Experimental results illustrate that compared with existing methods, the proposed scheme can effectively detect the salient objects. Particularly, we testify that, in our scheme, the precision of object recognition is proportional to image segmentation accuracy.**

***Index Terms*—Object Recognition; Graph Cut; Image Segmentation; SIFT; Energy Function**

I. INTRODUCTION

In the computer vision research field, image segmentation refers to the process of partitioning a digital image into multiple segments, which are made up of a set of pixels. The aim of image segmentation is to simplify and change the representation of an image into something that is more meaningful and easier for users to analyze. That is, image segmentation is typically utilized to locate objects and curves in images [1] [2]. Particularly, image segmentation is the process of allocating a tag to each pixel of an image such that pixels with the same tag sharing specific visual features. The results of image segmentation process can be represented as a set of segments which totally cover the whole image [3]. The pixels belonged to the same region are similar either in some characteristics or in some computed properties, which refer to the color, intensity, or texture. On the other hand, adjacent regions are significantly different with respect to the same characteristics.

The problems of image segmentation are great challenges for computer vision research field. As the time of the Gestalt movement in psychology, it has been known that perceptual grouping plays a powerful role in human visual perception. A wide range of computational vision problems could in principle make good use of segmented images, were such segmentations reliably and efficiently computable. For instance intermediate-level vision problems such as stereo and motion estimation require an appropriate region of support for correspondence operations. Spatially non-uniform regions of support can be identified using segmentation techniques. Higher-level problems such as recognition and image indexing can also utilize segmentation results in matching, to address problems such as figure-ground separation and recognition by parts [4-6].

As salient objects are important parts in images, hence, if they can be effectively detected, the performance of image segmentation can be promoted. Object recognition refers to locate collections of salient line segments in an image [7]. The object recognition systems are designed to correctly identify an object in a scene of objects, in the presence of clutter and occlusion and to estimate its position and orientation. Those systems can be exploited in robotic applications where robots are required to navigate in crowded environments and use their equipment to recognize and manipulate objects [8].

In this paper, the image segmentation is regarded as a graph cut problem, which is a basic problem in computer algorithm and theory. In computer theory, the graph cut problem is defined on data represented in the form of a graph $G = (V, E)$, where V and E represent the vertices and edges of the graph respectively, such that it is possible to cut G into several components with some given constrains. Graph cut method is widely used in many application fields, such as scientific computing, partitioning various stages of a VLSI design circuit and task scheduling in multi-processor systems [9] [10].

The main innovations of this paper lie in the following aspects:

(1) The proposed algorithm converts the image segmentation problem into graph cut problem, and the graph cut results can be obtained by an optimization process using energy function.

(2) In the proposed, the objects can be detected by computing the visual similarity between the segments of the testing images and the object types from the training images.

(3) A testing image is segmented into several segments, and each image segment is tested to find if there is a kind of object can match it.

The rest of the paper is organized as the following sections. Section 2 introduces the related works. Section 3 illustrates the proposed scheme for recognizing objects

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from images utilizing graph cut policy. In section 4, experiments are implemented to make performance evaluation. Finally, we conclude the whole paper in section 5.

II. Related Works

In this section, we will survey related works about this paper in two aspects, including 1) image segmentation and 2) graph cut based image segmentation.

Dawoud et al. proposed an algorithm that fuses visual cues of intensity and texture in Markov random fields region growing texture image segmentation. The main idea is to segment the image in a way that takes EdgeFlow edges into consideration, which provides a single framework for identifying objects boundaries based on texture and intensity descriptors [11].

Park proposed a novel segmentation method based on a hierarchical Markov random field. The proposed algorithm is composed of local-level MRFs based on adaptive local priors which model local variations of shape and appearance and a global-level MRF enforcing consistency of the local-level MRFs. The proposed method can successfully model large object variations and weak boundaries and is readily combined with well-established MRF optimization techniques [12].

Gonzalez-Diaz et al. proposed a novel region-centered latent topic model that introduces two main contributions: first, an improved spatial context model that allows for considering inter-topic inter-region influences; and second, an advanced region-based appearance distribution built on the Kernel Logistic Regressor. Furthermore, the proposed model has been extended to work in both unsupervised and supervised modes [13].

Nie et al. proposed a novel two-dimensional variance thresholding scheme to improve image segmentation performance is proposed. The two-dimensional histogram of the original and local average image is projected to one-dimensional space in the proposed scheme firstly, and then the variance-based criterion is constructed for threshold selection. The experimental results on bi-level and multilevel thresholding for synthetic and real-world images demonstrate the success of the proposed image thresholding scheme, as compared with the Otsu method, the two-dimensional Otsu method and the minimum class variance thresholding method [14].

Chen et al. proposes a new multispectral image texture segmentation algorithm using a multi-resolution fuzzy Markov random field model for a variable scale in the wavelet domain. The algorithm considers multi-scalar information in both vertical and lateral directions. The feature field of the scalable wavelet coefficients is modelled, combining with the fuzzy label field describing the spatially constrained correlations between neighbourhood features to achieve more accurate parameter estimation [15].

Han et al. presented a novel variational segmentation method within the fuzzy framework, which solves the problem of segmenting multi-region color-scale images of natural scenes. The advantages of the proposed segmentation method are: 1) by introducing the PCA descriptors, our segmentation model can partition color-texture images better than classical variational-based segmentation models, 2) to preserve geometrical structure of each fuzzy membership function, we propose a nonconvex regularization term in our model, and 3) to solve the segmentation model more efficiently, the authors design a fast iteration algorithm in which the augmented Lagrange multiplier method and the iterative reweighting are integrated [16].

Souleymane et al. designed an energy functional based on the fuzzy c-means objective function which incorporates the bias field that accounts for the intensity inhomogeneity of the real-world image. Using the gradient descent method, the authors obtained the corresponding level set equation from which we deduce a fuzzy external force for the LBM solver based on the model by Zhao. The method is fast, robust against noise, independent to the position of the initial contour, effective in the presence of intensity inhomogeneity, highly parallelizable and can detect objects with or without edges [17].

Liu et al. proposed a new variational framework to solve the Gaussian mixture model (GMM) based methods for image segmentation by employing the convex relaxation approach. After relaxing the indicator function in GMM, flexible spatial regularization can be adopted and efficient segmentation can be achieved. To demonstrate the superiority of the proposed framework, the global, local intensity information and the spatial smoothness are integrated into a new model, and it can work well on images with inhomogeneous intensity and noise [18].

Wang et al. presented a novel local region-based level set model for image segmentation. In each local region, the authors define a locally weighted least squares energy to fit a linear classifier. With level set representation, these local energy functions are then integrated over the whole image domain to develop a global segmentation model. The objective function in this model is thereafter minimized via level set evolution [19].

Wang et al. presented an online reinforcement learning framework for medical image segmentation. A general segmentation framework using reinforcement learning is proposed, which can assimilate specific user intention and behavior seamlessly in the background. The method is able to establish an implicit model for a large state-action space and generalizable to different image contents or segmentation requirements based on learning in situ [20].

In recent years, several researchers utilized the Graph Cut technology to implement the image segmentation, and the related works are illustrated as follows.

Zhou et al. present four technical components to improve graph cut based algorithms, which are combining both color and texture information for graph cut, including structure tensors in the graph cut model, incorporating active contours into the segmentation process, and using a "softbrush" tool to impose soft constraints to refine problematic boundaries. The integration of these components provides an interactive

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segmentation method that overcomes the difficulties of previous segmentation algorithms in handling images containing textures or low contrast boundaries and producing a smooth and accurate segmentation boundary [21].

Chen et al. proposed a novel synergistic combination of the image based graph cut method with the model based ASM method to arrive at the graph cut -ASM method for medical image segmentation. A multi-object GC cost function is proposed which effectively integrates the ASM shape information into the graph cut framework The proposed method consists of two phases: model building and segmentation. In the model building phase, the ASM model is built and the parameters of the GC are estimated. The segmentation phase consists of two main steps: initialization and delineation [22].

Wang et al. present a novel method to apply shape priors adaptively in graph cut image segmentation. By incorporating shape priors adaptively, the authors provide a flexible way to impose the shape priors selectively at pixels where image labels are difficult to determine during the graph cut segmentation. Further, the proposed method integrated two existing graph cut image segmentation algorithms, one with shape template and the other with the star shape prior [23].

Yang et al. proposed an unsupervised color-texture image segmentation method. To enhance the effects of segmentation, a new color-texture descriptor is designed by integrating the compact multi-scale structure tensor, total variation flow, and the color information. To segment the color-texture image in an unsupervised and multi-label way, the multivariate mixed student's t-distribution is chosen for probability distribution modeling, as MMST can describe the distribution of color-texture features accurately. Furthermore, a component-wise expectation-maximization for MMST algorithm is proposed, which can effectively initialize the valid class number. Afterwards, the authors built up the energy functional according to the valid class number, and optimize it by multilayer graph cuts method [24].

III. The Proposed Scheme

A. Problem Statement

In this paper, the problem of image segmentation is converted into the problem of graph cut. Let an undirected and connected graph $G=(V,E)$ where $V=\{1,2,...,n\}$ and $E\subset\{(i,j),1\le i<j\le n\}$ are satisfied. Let the edge weights $w_{ij}=w_{ji}$ be given such that $w_{ij}=0$ for $(i,j)\notin E$, and in particular, let $w_{ii}=0$. The graph cut problem is to find a partition results $(V_1,V_2,\cdots,V_N)$ of V where the condition $V_1\bigcup V_2\bigcup\cdots\bigcup V_N$ is satisfied.

In the problem image segmentation, the nodes in V denotes the pixels of images and the edge weight is estimated by computing the distance between two pixels. Particularly, the graph cut based image segmentation results can be obtained by a subset of the edges of the edge set E. There are several methods to calculate the quality of image segmentation results. The main idea is quite simple, that is, we want the pixels in a same component to be similar, and the pixels in different components to be dissimilar. Thai is to say that edge between two nodes which are belonged to the same component should have lower value of weights, and edges which are located between nodes in different components should have higher value of weights.

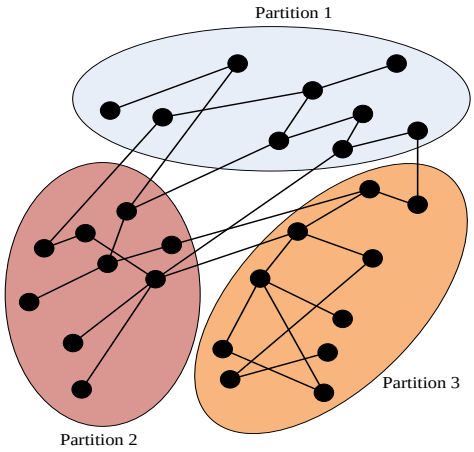


Figure 1. Explaination of the graph cut problem

B. Graph Cut Based Image Segmentation

In the proposed, the main innovation lies in that we regard the graph cut based image segmentation problem as an energy minimization problem. Therefore, given a set of pixels P and a set of labels L, the object is to seek a label $l:P\to L$, which can minimize the following equation.

$$E(l)=\sum_{p\in P}R_p(l_p)+\sum_{p\in P,q\in N_p}C_p^q\cdot(l_p,l_q) \qquad (1)$$

where N_p denotes the pixel set which is belonged to the neighborhood of p, and $R_p(l_p)$ refers to the cost of allocating the label l_p to p. Moreover, $C_p^q\cdot(l_p,l_q)$ denotes the cost of allocate the label l_p and l_q to p and q respectively. Afterwards, the proposed energy function is defined in Eq. 2.

$$E=\sum_{p\in P}\left(\alpha_1\cdot D_p(f_p)+\alpha_2\cdot S_p(x_o)\right)+\sum_{p\in P,q\in N_p}\alpha_3\cdot C_q^p(l_p,l_q) \qquad (2)$$
$$s.t.\ \alpha_1+\alpha_2+\alpha_3=1$$

In Eq. 2, the parameters α_1, α_2 and α_3 denote the weight of data stream D_p, shape term D_p, and the boundary term respectively. Furthermore, the above modules can be represented as the following forms.

$$D_p(l_p)=\begin{cases}-LogP(I_p|O), l_p=object\ label\\ -LogP(I_p|B), l_p=background\ label\end{cases} \qquad (3)$$

$$C_q^p(l_p,l_q)=\frac{\varphi(l_p,l_q)}{dis(p,q)}\cdot\exp\left(\frac{-(I_p-I_q)^2}{2\vartheta^2}\right) \qquad (4)$$

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$$\varphi(l_p, l_q) = \begin{cases} 1, l_p \neq l_q \\ 0, l_p = l_q \end{cases} \quad (5)$$

where I_p denotes the intensity of the pixel p, and $P(I_p|O)$, $P(I_p|B)$ represents the probability of intensity for pixel p which is belonged to the object and the background intensity. $dis(p,q)$ refers to the distance between pixel p and q, and ϑ denotes the standard deviation of the intensity differences of the neighbors.

Next, based on the graph cut algorithm, the graph G is represented as $G = (V, E)$, where V and E refer to a set of nodes and a set of weighted edges. The graph cut problem concentrate on seek a cut C with minimal cost $|C|$, which is the sum of the weight for all the edges. Following the above description, the graph cut process *with the cost* $|C|$ which is equal to $E(l)$ is implemented by the following weight configuration as follows.

$$W_q^p = \alpha_3 \cdot C_q^p \quad (6)$$

$$W_t^p = \Gamma - \left(\alpha_2 \cdot D_p(t) + \alpha_3 \cdot S_p(t)\right) \quad (7)$$

where Γ refers to a constant which can ensure the weight W_t^p be positive, and t belongs to the set of labels and the weight of which is W_t^p

C. Object Recognition Algorithm

From the former section, a testing image is segmented into several segments, next, for each segment we will try to match it in a pre-set training image dataset which includes many image segments, and the segments belonged to the same object types are collected together.

We use corel5k dataset as to construct training dataset, which consists of 5,000 images which are divided into 50 image classes with 100 images in each class. Each image in the collection is reduced to size 117×181 (or 181×117). We use all the 5,000 images as training dataset (100 per class). Each image is treated as a collection of 20×20 patches obtained by sliding a window with a 20-pixel interval, resulting in 45 patches per image. Moreover, we utilize the 128-dimension SIFT descriptor computed on 20×20 gray-scale patches. Furthermore, we add additional 36-dim robust color descriptors which have been designed to complement the SIFT descriptors extracted from the gray-scale patches. Afterwards, we run k-means on a collection of 164D features to learn a dictionary of 256 visual words.

For a test image I, we partition it into several blocks and map each image block to a visual word through bag of visual words model. Thus, similar to documents, images can be represented as a set of visual words (denoted as d_I). For a object type O_i, the similarity between image I and the object type tag O_i can be calculated as follows.

$$Sim(d_I, O_i) = \frac{\sum_{x=1}^{N}\sum_{y=1}^{M} S(d_I^x, O_i^y)}{N \cdot M} \quad (8)$$

Afterwards, the objects in the test image can be detected by the following equation.

$$Object(I) = \arg\min_i Sim(d_I, O_i) \quad (9)$$

Therefore, the objects with the minimized values in Eq. 9 are regarded as the objects in image I

IV. EXPERIMENTS

In this section, we make performance evaluation utilizing three image dataset, which are 1) MIT Vistex [25], 2) BSD 300 [26] and 3) SODF 1000 [27]. As the object recognition and image segmentation are quite subjective, the performance measuring metric is very important. In this experiment, PRI and NPR are used as performance evaluation metric to make quantitative evaluation. PRI refers to the probabilistic rand index and NPR denotes the normalized probabilistic rand. Particularly, the values of PRI and NPR range from $[0,+1]$ and from $[-\infty,+1]$ respectively. Larger value of the two metrics means that the image segmentations are much closer to the ground truths.

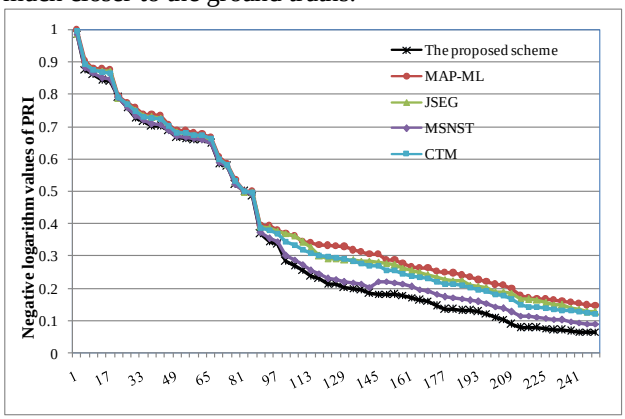


Figure 2. Negative logarithm values of PRI for different methods.

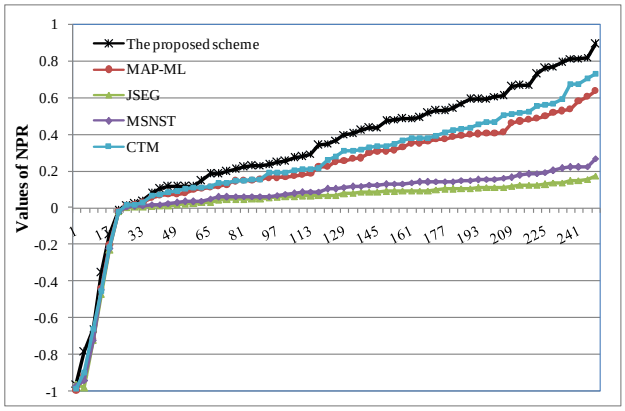


Figure 3. Values of NPR for different methods.

Afterwards, to testify the performance of the proposed graph cut based image segmentation approach, other four existing unsupervised color-texture image segmentation methods are compared. These four methods contain the

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TABLE I. OVERALL PERFORMANCE COMPARISON FOR DIFFERENT DATASETS.

Dataset	Type	Metric	CTM	MSNST	JSEG	MAP-ML	The proposed scheme
MIT Vistex	Mean	PRI	0.764	0.753	0.742	0.791	0.823
		NPR	0.292	0.436	0.347	0.401	0.444
	Variance	PRI	0.129	0.124	0.147	0.119	0.118
		NPR	0.366	0.272	0.383	0.318	0.256
BSD 300	Mean	PRI	0.804	0.848	0.736	0.790	0.873
		NPR	0.293	0.422	0.379	0.442	0.464
	Variance	PRI	0.134	0.133	0.153	0.115	0.121
		NPR	0.351	0.287	0.398	0.336	0.243
SODF 1000	Mean	PRI	0.725	0.766	0.726	0.748	0.810
		NPR	0.278	0.382	0.319	0.430	0.435
	Variance	PRI	0.122	0.132	0.133	0.122	0.118
		NPR	0.328	0.270	0.377	0.310	0.261

TABLE II. COMPARISON OF TIME COST FOR DIFFERENT APPROACHES.

Approaches	CTM	MSNST	JSEG	MAP-ML	The proposed scheme
Running time(s)	223.7	247.8	35.4	136.2	105.3
Running platform	Java	C++	Java	Matlab	C++

methods for unsupervised segmentation of color-texture regions in images or video (JSEG) [28], maximum a posteriori and maximum likelihood estimation (MAP-ML) [29], compression-based texture merging(CTM) [30], and MSNST which integrates the multi-scale nonlinear structure tensor texture and Lab color adaptively [31].

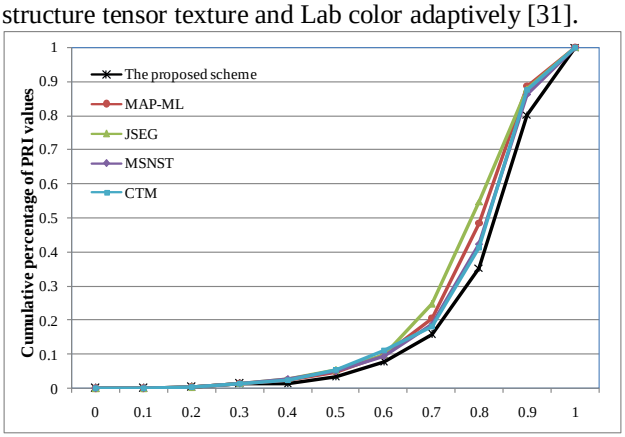


Figure 4. Cumulative percentage of PRI score for different methods.

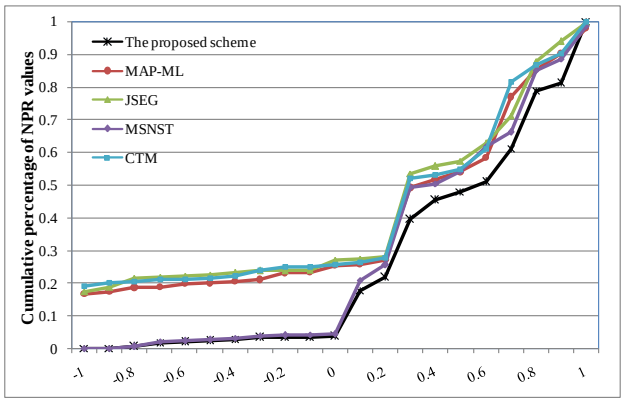


Figure 5. Cumulative Percentage of NPR Values for different methods.

Afterwards, the mean values and variance values of PRI and NRP under the above approaches are given using the BSD 300 dataset (shown in Table.1).

All the experiments are conducted on the PC with Intel Corel i5 CPU, the main frequency of which is 2.9GHz. The memory we used is the 8GB DDR memory with 1600MHz, and the hard disk we utilized is 500GB SSD disk. Moreover, the graphics chip is the NVIDIA Optimus NVS5400M. Based on the above hardware settings, the algorithm running time are compared in Table 2 as follows.

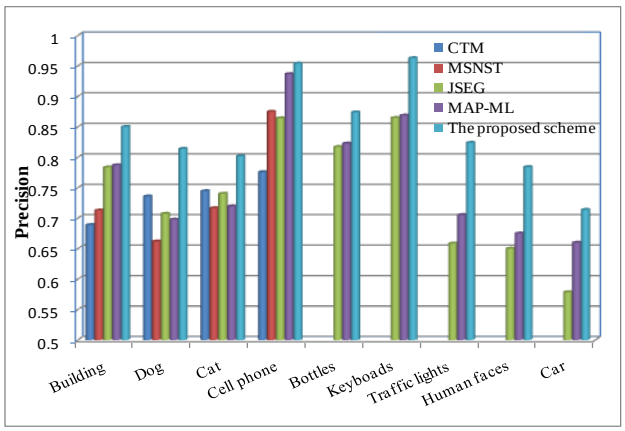


Figure 6. Precision of object recognition for different kinds of objects.

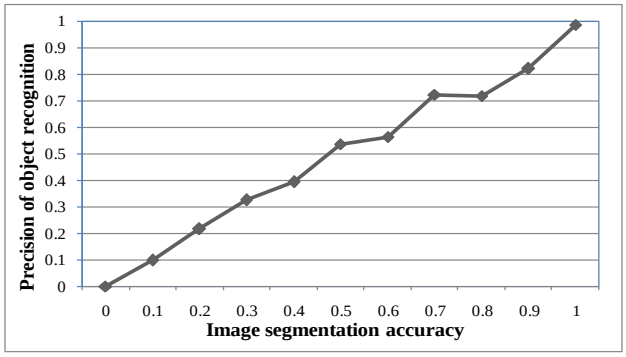


Figure 7. Relationship between precision of object recognition and image segmentation accuracy.

From Table 2, it can be seen that the proposed scheme is obviously faster than other approaches except JSEG. However, the performance of JPEG is the worst of the five methods. Hence, the proposed scheme is very valuable.

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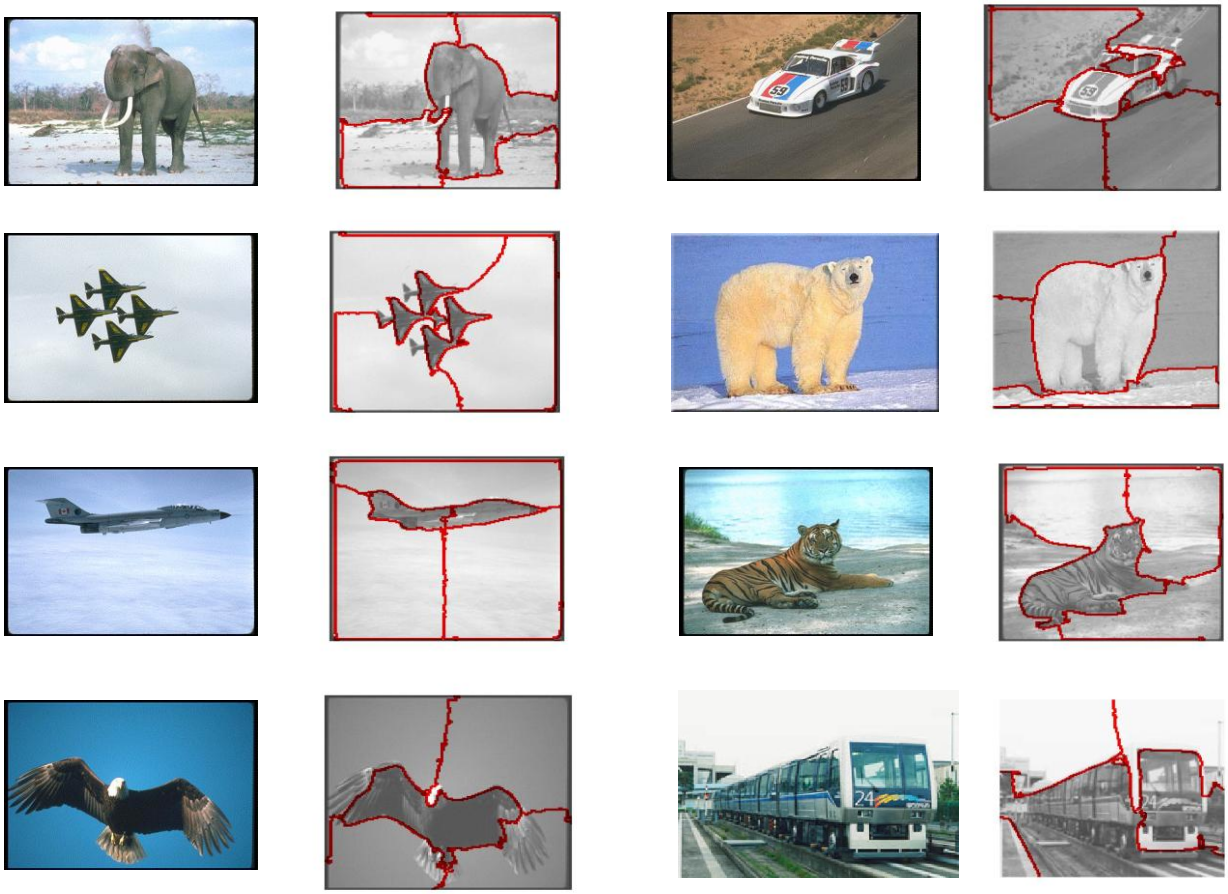


Figure 8. Example of the object recognition results by the proposed image segmentation algorithm

In the following parts, we will test the influence of image segmentation accuracy to object recognition. Firstly, experiments are conducted to show the precision of object recognition for different kinds of objects, and the results are shown in Fig. 6.

Secondly, the relationship between precision of object recognition and image segmentation accuracy is shown in Fig. 7.

As is shown in Fig. 7, precision of object recognition is proportional to image segmentation accuracy. Therefore, image segmentation module in the proposed is very powerful in the object recognition process.

From the above experimental results, it can be seen that the proposed scheme is superior to other two schemes. The main reasons lie in the following aspects:

(1) The proposed scheme converts the image segmentation problem into graph cut problem, and we obtained the graph cut results by an optimization process. Moreover, the objects can be detected by computing the visual similarity between the segments of the testing images and the object types from the training images.

(2) For the JSEG algorithm, there is a major problem which is caused the varying shades due to the illumination. However, this problem is difficult to handle because in many cases not only the illuminant component but also the chromatic components of a pixel change their values due to the spatially varying illumination.

(3) The MAP-ML algorithm should be extended to segment image with the combination of motion information, and the utilization of the model for specific object extraction by designing more complex features to describe the objects.

(4) The CTM scheme should be extended to supervised scenarios. As it is of great importance to better understand how humans segment natural images from the lossy data compression perspective. Such an understanding would lead to new insights into a wide range of important problems in computer vision such as salient object detection and segmentation, perceptual organization, and image understanding and annotation.

(5) The performance of MSNST is not satisfied, because the proposed method is the compromise between high segmentation accuracy and moderate computation efficiency. Particularly, the parameter setting in this scheme is too complex and more discriminative segmentation process should be studied in detail.

V. CONCLUSIONS

In this paper, we proposed an effective object recognition algorithm based on image segmentation. The image segmentation problem is converted into the graph cut problem, and then the graph cut results can be computed by estimating the probability of intensity for a given pixel which is belonged to the object and the background intensity. In order to find the salient objects

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we compute the visual similarity between the segments of the testing images and the object types deduced from the Corel5K image dataset.

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