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Image Co-Segmentation and Efficiency Saliency Detection

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Abstract: Today there is a massive attempt to exclude the same object from different images. Such problem is not an easy task as it seems, furthermore the algorithm which is presented today is not 100% accurate even though it is efficient. A novel interactive image cosegmentation algorithm using likelihood estimation and higher order energy optimization is proposed for extracting common foreground objects from a group of related images. Our approach introduces the higher order clique's, energy into the cosegmentation optimization process successfully. A region-based likelihood estimation procedure is first performed to provide the prior knowledge for our higher order energy function. Further extended the work for image saliency detection which is used to automatically locate the content that draws a viewer's attention in the early stage of visual processing.

Keywords: Co-segmentation, Saliency Segmentation, Feature Extraction, Energy optimization

I. INTRODUCTION

co-segmentation is commonly referred as jointly partitioning multiple images into foreground and background components. The idea of co-segmentation is first introduced by Rother *et al.* [5] where they simultaneously segment common foreground objects from a pair of images. The co-segmentation problem has attracted much attention in the last decade, most of the co-segmentation approaches [2], [3], [8], [10], [13], [18], [23], [24] are motivated by traditional Markov Random Field (MRF) based energy functions, which are generally solved by the optimization techniques such as linear programming [8], dual decomposition [18] and network flow model [10]. The main reason may be that the graph-

cuts and MRF methods [4], [33] work well for image segmentation and are also widely used to solve the combinatorial optimization problems in multimedia processing. In recent years, with the emergence of discrete optimization, many low-level computer vision problems are solved via energy minimization algorithms, such as graph cuts, [1, 2] tree reweighted message passing [3, 4] and belief propagation. [5, 6] These algorithms allow us to perform approximate inference on graphical models, i.e., by maximizing a posterior probability on Markov Random Fields. Applications of these energy minimization methods include image segmentation, stereo, denoising, and etc. Within such framework, one usually seeks the labeling L that minimizes the energy,

$$E(L) = \sum_{p \in P} D_p(L_p) + \lambda \sum_{p, q \in N} V_{p, q}(L_p, L_q)$$

Here, D_p measures labeling preference of pixel p , and $V_{p, q}$ encourages spatial coherence by penalizing discontinuities between neighboring pixels (p, q) . The symbol P denotes pixel set, and N stands for set of neighboring pairs. The parameter λ controls strength of smoothness. However, this model assumes that the energy is represented in terms of unary and pairwise potentials, which severely restricts its representational power, as it is too local to capture rich statistics of natural scenes. We construct higher-order clique as a composed group of three parts: the foreground region, the background region and the over-segmentation region, which considers the correspondence between the over-segmentation region and the labeled region. This strategy makes our framework effective enough in realistic scenarios, instead of a simple foreground/background appearance histogram model. Additionally, our higher-order energy efficiently utilizes the statistical information on a group of pixels by estimating the segmentation quality on higher-order cliques. Compared to existing image co-segmentation methods, the proposed approach offers the following contributions. performance.

A novel higher-order clique construction method is proposed using the estimated foreground/background regions and the regions of original images.

A new region likelihood estimation method is presented, which provides enough prior information for higher-order energy item for generating final co-segmentation results.

We further propose a method that leverages saliency estimation and automatically generates thumbnails for stereoscopic photo pairs. An efficient stereo saliency detection algorithm is proposed.

It is based on discriminative saliency cues such as edges and stereoscopic disparities. The produced two stereo saliency maps are consistent and reliable. Finally, generate results and show that saliency segmentation provides more accurate image segmentation. The rest of the paper is organized as follows. Introduce the background and related work in Section II. The proposed work in Section III to support the efficiency of our proposed algorithm. Section IV will discuss about the obtained experimental results and finally, Section V concludes the paper and gives the future work.

II. RELATED WORK

A. Optimization for image segmentation

Image segmentation has long been studied. In recent years, a bulk of work emerges that solves segmentation problem by minimizing a discrete energy, where each pixel is assigned a certain label. Graph cuts employed the min-cut/max-flow algorithms to minimize the proposed energy that consists of a data term and a smoothness term, as shown in Eqn. 1, which is widely used to achieve image segmentation. Kolmogorov et al. provided necessary and sufficient conditions for such energy function. Geometric properties of regions formed by graph cuts were described. A large variety of interactive segmentation methods based on graph cuts have also been developed these years. In general, none of them is superior to all the others. And some methods may be more suitable for solving particular segmentation problems than others. Sometimes, automatic methods are not sufficient to locate the object. In this sense, interactive methods are better off because they combine user interactions that can easily locate the object. Usually, an interactive graph-based segmentation method contains the following steps: 1) calculate user preferences that provide cues by the user and 2) generate an optimal solution according to user preferences. In situations where automatic segmentation is difficult and cannot guarantee correctness and reliability, the interactive methods are best adopted. Among these methods, Ref. 25-27 admitted shape priors into interactive graph cuts, Ref. 28-30 improved running time of such methods, and Ref. 31-32 applied the interactive methods in medical and some other applications. GrabCut by Rother et al. extracted the foreground of an image, by utilizing a bounding box provided by the user that roughly holds the foreground, and then ran graph cuts iteratively. In the random walker algorithm, some pixels should be pre-classified by the user. Then an unclassified pixel is assigned a label when a random walker has been given the greatest probability on traversing first to the classified pixel from the unclassified pixel. Graph cuts can obtain the optimal solution for binary problems. However, when each pixel can be assigned many labels, finding the solution can be computationally expensive. To address this problem, moving making algorithms based on graph cuts emerges, which can efficiently solve multi-label segmentation problem. The energy form in Eqn. 1 only describes constraints between pixel pairs. In order to capture rich statistics of the image, Zeng et al. [14] introduced a framework to integrate non-local statistics into the higher-order Markov Random Fields, using additional latent variables to represent the intrinsic dimensions of the higher-order cliques. Jain et al. solved the higher-order clustering problem by combining attributes of both decomposition of higher-order similarity measures for use in spectral clustering and explicitly use low-rank matrix representations. Fix et al. focused on the higher-order labeling problem by addressing the sum-of submodular functions. Semantic segmentation using context models is also extended from pairwise relationship between objects to higher-order semantic relations. Ref. 7, 9, 13 added a clique term in the pairwise model to enforce pixels within a clique to take the same label. Usually, the clique is a set of pixels. Ref. 38 introduced an interactive segmentation method using non-parametric higher-order learning algorithm. In their method, they designed two quadratic cost functions of pixel and region likelihoods in a multi-layer graph and estimated them simultaneously. Our method is more related to Ref. 38. The main idea of our algorithm is that the property of cliques and pixels can supplement each other, and we iteratively optimize pixel labeling and clique potentials. The main difference from Ref. 38 is that in our method, each pixel is related to multiple cliques, whereas in Ref. 38 each pixel was linked to one specified region.

B. Saliency Detection

Image saliency detection aims at automatically locating the content that draws a viewer's attention in the early stage of visual processing. It has been extensively studied for decades. Relevant methods in general can be categorized as either bottom-up or top-down approaches. Top-down approaches [21], [22], [23] are goal-directed and require an explicit understanding of image contexts. Supervised learning is therefore frequently adopted. Most of the saliency detection methods [45], [46] are based on bottom-up visual attention mechanisms, which are independent of the knowledge of the image content. The saliency map can also be inferred using the combination of multiple features, such as center-surround methods [24], region contrast methods [25], [26], [27], global methods [28], [29], [30] and background prior based methods [31]. There has been recent interest in identifying common salient regions from multiple related images [32], [33], [34]. In these works, the appearance and structural information of objects across multiple images are treated as additional priors in

saliency estimation. Interestingly, stereo image pairs are also highly correlated, conforming to the basic assumption of co-saliency. However, stereo image pairs have binocular viewing constraints that are able to offer better indicators, such as depth cues, for identifying noticeable regions. There is no co-saliency method that makes use of depth cues. Compared with the enormous amount of work on 2-D image saliency estimation, saliency detection for 3-D images is a far less touched topic. Niu *et al.* [35] present a stereo saliency model that leverages stereopsis, which provides depth cues and plays an important role in the human vision system. Cropping-based thumbnail creation methods identify a rectangular area encompassing attention-catching objects, which are usually determined by the saliency map. Suh *et al.* [1] integrate classic saliency detection [24] with a greedy window search algorithm for automatic thumbnail cropping. A similar idea is also explored in [2]. In [3], scale-dependent saliency, motivated by [36], is combined with an objectness measure [37] for achieving scale and object aware thumbnail creation. Our method introduces a stereo saliency detection method by considering both saliency stimulus and stereopsis, which guarantees the consistency between the two stereo saliency maps. This helps our proposed method to produce high-quality images.

III. PROPOSED APPROACH

A. Overview

Our co-segmentation procedure includes two main steps. The first step is a fast but effective likelihood estimation process, which calculates the probabilities of pixels belonging to foreground/background over entire dataset according to user scribbles. The estimated likelihood offers a rough estimation for foreground/background and is fed into next step as prior knowledge. In the second stage, a higher-order energy based co-segmentation function is proposed to obtain final accurate co-segmentation results on a group of images, which is based on higher order cliques. Our

higher-order cliques are constructed from a set of foreground and background regions by user scribbles, where all the regions in each image are matched to produce better co-segmentation performance. Additionally, our approach considers the quality of segmentation in higher-order energy to obtain more accurate estimations of foreground/background.

B. Likelihood Estimation

Given a group of images $\{I^1, \dots, I^n\}$ and the user scribbles that indicate foreground or background objects, we first compute pixel likelihood x_k^i for foreground/background in image I^1 . The likelihood of pixel x_k^i is denoted by $x_{k,l}^i$ where l is a label indicating foreground (1) or background (0) and k is the index value of x_k^i . We compute the likelihoods of regions instead of pixels for computational efficiency. Each input image I^i of the group is divided into regions $r_s^i \in R^i$ using the over-segmentation methods such as mean shift [1] or efficient graph [6] method. For each region r_s^i , the region likelihoods of foreground and background are defined as $z_{s,l}^i$ which is further formulated in a quadratic energy function as follows:

$$F_l^i = F_1 + F_2$$

$$= \lambda^i \sum_{s=1}^{N(R^i)} (z_{s,l}^i - \epsilon_{s,l}^i)^2 + \sum_{s,s'=1}^{N(R^i)} w_{s,s'}^i (z_{s,l}^i - z_{s',l}^i)^2$$

where the first term F_1 defines an unary constraint that each region tends to have the initial likelihood $\epsilon_{s,l}^i$ estimated through the appearance similarity to foreground/background. The second term F_2 gives the interactive constraint that all regions of the whole image should have same likelihood when their representative colors are similar.

C. Higher-Order Energy Co-Segmentation

Via our likelihood estimation, we have a fast and rough estimate for foreground/background in each image. For generating more accurate co-segmentation results, we further propose a higher-order energy based co-segmentation function. In order to simultaneously segment a group of input images

$\{I^1, \dots, I^n\}$ with the labeled images T , we first build a global term $E_{\text{global}}\{I^1, \dots, I^n, T\}$ to match all the images with the labeled images T . The proposed energy of our co-segmentation algorithm is expressed as follows:

$$\mathcal{F} = \sum_{i=1}^n (\epsilon_1^i E_{\text{unary}}^i + \epsilon_2^i E_{\text{pairwise}}^i) + E_{\text{global}}(I^1, \dots, I^n, T)$$

where E_{unary}^i and E_{pairwise}^i denote unary term and pairwise term respectively and the global term E_{global} is proposed to match all the input images $\{I^1, \dots, I^n\}$ with labeled images T .

The scalars ϵ weight various terms. The unary term E_{unary}^i and the pairwise term E_{pairwise}^i for image I^i are defined as follows:

$$E_{\text{unary}}^i = \sum_k -\log(\pi_{k,1}^i) \cdot \phi(x_k^i) - \log(\pi_{k,0}^i) \cdot (1 - \phi(x_k^i))$$

$$E_{\text{pairwise}}^i = \sum_{k,k' \in \mathbb{N}} \|c_k^i - c_{k'}^i\| \cdot |\phi(x_k^i) - \phi(x_{k'}^i)|$$

our co-segmentation energy function is given by,

$$\mathcal{F} = \sum_{i=1}^n \left\{ \sum_k \left(\exp^{-\pi_{k,1}^i} \phi(x_k^i) + \exp^{-\pi_{k,0}^i} (1 - \phi(x_k^i)) \right) + \sum_{k,k' \in \mathbb{N}} \|c_k^i - c_{k'}^i\| \cdot |\phi(x_k^i) - \phi(x_{k'}^i)| + E_{\text{high}}(R^i, \mathfrak{S}) \right\}. \quad ($$

D. Stereo Saliency Detection

In this section, we present the first half of our thumbnail generation system, the stereo saliency detection step, which aims at identifying the most important regions from input stereo image pairs. The input to our method is a pair of $m \times n$ stereo images, $\{IL; IR\}$, and a disparity map, D , which can be computed by any stereo algorithm such as the one in [38], [39]. The output of our saliency algorithm is a pair of corresponding stereo saliency maps $\{SL; SR\}$, where the intensity of each pixel represents the probability of that pixel being visually important.

E. Saliency Based on Disparity and Edges

Edges constitute an important type of saliency stimuli. We further have an important observation that disparity boundaries are able to reveal the location of occlusion boundaries, which very often correspond to physical object boundaries. This phenomenon can be easily observed. Edges and disparity boundaries provide complementary information. Edges precisely outline object contours. However, they are often too dense and appear inside objects as well. On the contrary, disparity boundaries typically do not cover entire object boundaries due to errors in disparity estimation, but are relatively sparse and able to omit unnecessary details. These observations motivate us to integrate these two types of cues together for stereo saliency detection. For a stereo image $I_k (k \in \{L, R\})$, we first compute an edge response $E_k(x)$ for pixel x . The value of $E_k(x)$ is normalized to $[0, 1]$ with a higher value representing a higher probability of the presence of an object boundary at pixel x . The edge probability map E_k is found using the edge detection technique, which has shown good performance in object contour detection. The edge response map E_k and disparity map D are integrated into a disparity-edge map $b E_k$ as follows:

$$\hat{E}_k = \phi \left(E_k \cdot (\lambda + \phi(\nabla D)) \right)$$

where ∇D represents the gradient magnitude of the disparity map D and $\phi(\cdot)$ denotes the dilation operation with the radius typically set to 5 pixels. There usually exist discontinuities in disparity along object boundaries. Therefore, ideally, the gradient of disparity should have a large magnitude around object boundaries. In practice, a locally maximal gradient magnitude may not coincide exactly with an object boundary due to approximations in disparity calculation. We dilate disparity gradients and set the

value of λ as small as 0.2. The result is a sparse disparity-edge map \hat{E}_k , where local maximal values precisely coincide with object boundaries.

IV. RESULTS

The below figure 1 shows the input figure for which co-segmentation and Saliency segmentation is performed. The results are shown in matlab tool.

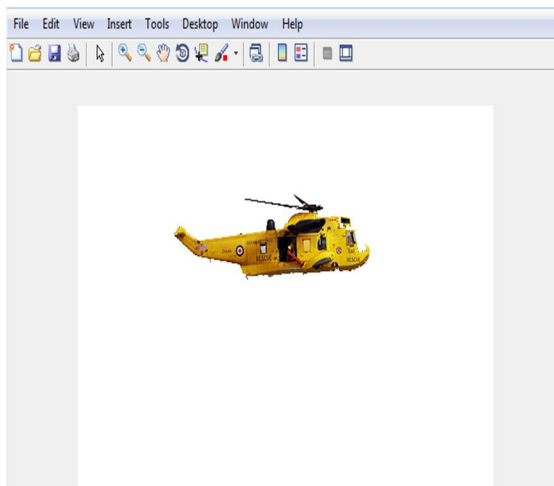


Fig 1.Input Image.

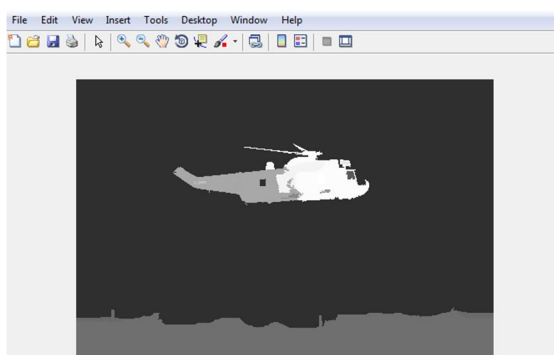


Fig 2. Co-Segment image



Fig 3. Saliency Segmentation

V. CONCLUSION

We have presented a novel interactive co-segmentation approach using the likelihood estimation and high-order energy optimization to extract the complicated foreground objects from a group of related images. A likelihood estimation method is developed to compute the prior knowledge for our higher-order co-segmentation energy function. Our higher-order cliques are built on a set of foreground and background regions obtained by likelihood estimation. Then our co-segmentation process from a group of images is performed at the region level through our higher-order cliques energy optimization. The energy function of our higher-order cliques

can be further transformed into a second-order boolean function and thus the traditional graphcuts method can be used to solve them exactly. Our algorithm has been evaluated in the performance of the stereo saliency detection algorithm. Our experiments and user studies have demonstrated that the proposed stereo saliency detection algorithm is able to produce more accurate results than co-segmentation results.

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