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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 partitioningmultiple images into foreground and backgroundcomponents. The idea of co-segmentation is first introduced byRother *et al*. [5] where they simultaneously segment commonforeground objects from a pair of images. The co-segmentationproblem has attracted much attention in the last decade, mostof 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 bythe optimization techniques such as linear programming [8],dual decomposition [18] and network flow model [10]. Themain reason may be that the graph-

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

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

Here, *Dp*measures labeling preference of pixel *p*, and *Vp,q* encourages spatial coherence by penalizing discontinuities between neighboring pixels (*p*, *q*). The symbol *P* denotespixel set, and *N* stands for set of neighboring pairs. Theparameter λ controls strength of smoothness. However, thismodel assumes that the energy is represented in terms ofunary and pairwise potentials, which severely restricts itsrepresentational power, as it is too local to capture richstatistics of natural scenes.We construct higher-orderclique as a composed group of three parts: the foreground region,the background region and the over-segmentation region, whichconsiders the correspondence between the over-segmentation region and the labeled region. This strategy makes our frameworkeffective enough in realistic scenarios, instead of a simpleforeground/background appearance histogram model. Additionally,our higher-order energy efficiently utilizes the statistical informationon a group of pixels by estimating the segmentationquality on higher-order cliques.Compared to existing image co-segmentation methods, theproposed approach offers the following contributions.
performance.

A novel higher-order clique construction method is proposedusing 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-orderenergy item for generating final co-segmentation results.

We further propose a method that leverages saliency estimationand automatically generates thumbnails for stereoscopicphoto pairs.

An efficient stereo saliency detection algorithm is proposed.

It is based on discriminative saliency cues suchas edges and stereoscopic disparities. The produced twostereo saliency maps are consistent and reliable. Finally generate results and show that saliency segmentation provide more accurate image segmentation.
The rest of the paper is organized as follows. introducesthe background and related workin Section II. The proposed work in Section III to support theefficiency of our proposed algorithm.Section IV will discuss about the obtained experimental results and Finally, Section V concludesthe 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 byminimizing a discrete energy, where each pixel is assigned acertain label. Graph cuts employed the min-cut/max-flowalgorithms to minimize the proposed energy that consistinga data term and a smoothness term, as shown in Eqn. 1,which is widely used to achieve image segmentation. Kolmogorovet al. provided necessary and sufficient conditionsfor such energy function. Geometric properties of regionsformed by graph cuts were described. A largevariety of interactive segmentation methods based on graphcuts 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 arenot sufficient to locate the object. In this sense, interactivemethods are better off because they combine user interactionsthat can easily locate the object. Usually, an interactivegraph based segmentation method contains the following steps: 1) calculate user preferences that provide cues by theuser and 2) generate an optimal solution according to userpreferences. In situations where automatic segmentation is difficult and cannot guarantee correctness and reliability, theinteractive methods are best adopted. Among these methods,Ref. 25-27 admitted shape priors into interactive graphcuts, Ref. 28-30 improved running time of such methods,and Ref. 31-32 applied the interactive methods in medicaland some other applications. Grabcut by Rother et al. extractedthe foreground of an image, by utilizing a boundingbox 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 randomwalker has been given the greatest probability on traversingfirst 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 algorithmsbased on graph cuts emerges, which can efficiently solvemulti-label segmentation problem.The energy form in Eqn. 1 only describes constraints betweenpixel pairs. In order to capture rich statistics of theimage, Zeng et al.[14] introduced a framework to integratenon-local statistics into the higher-order Markov RandomFields, using additional latent variables to represent the intrinsicdimensions of the higher-order cliques. Jain et al.solved the higher-order clustering problem by combiningattributes of both decomposition of higher-order similaritymeasures for use in spectral clustering and explicitly uselow-rank matrix representations. Fix et al. focused on the higher-order labeling problem by addressing the sum-of submodularfunctions. Semantic segmentation using context models is also extended from pairwise relationship betweenobjects to higher-order semantic relations. Ref. 7,9,13added a clique term in the pairwise model to enforce pixelswithin clique to take the same label. Usually the clique isa set of pixels. Ref. 38 introduced an interactive segmentationmethod using non-parametric higher-order learning algorithm.In their method, they designed two quadratic costfunctions of pixel and region likelihoods in a multi-layergraph and estimated them simultaneously. Our method ismore related to Ref. 38. The main idea of our algorithm isthat the property of cliques and pixels can supplement eachother, and we iteratively optimize pixel labeling and clique potentials. The main difference from Ref. 38 is that in ourmethod, each pixel is related to multiple cliques, whereas inRef. 38 each pixel was linked to one specified region.

B. Saliency Detection

Image saliency detection aims at automatically locating the contentthat draws a viewer’s attention in the early stage of visualprocessing. It has been extensively studied for decades. Relevantmethods in general can be categorized as either bottom-up or topdownapproaches. Top-down approaches [21], [22], [23] are goaldirectedand require an explicit understanding of image contexts.Supervised learning is therefore frequently adopted. Most ofthe saliency detection methods [45], [46] are based on bottomupvisual attention mechanisms, which are independent of theknowledge of the image content. The saliency map can alsobe 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 basedmethods [31].There has been recent interest in identifying common salientregions from multiple related images [32], [33], [34]. In theseworks, the appearance and structural information of objects acrossmultiple 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 areable to offer better indicators, such as depth cues, for identifyingnoticeable regions. There is no co-saliency method that makes useof depth cues.Compared with the enormous amount of work on 2-D imagesaliency estimation, saliency detection for 3-D images is a farless touched topic. Niu*et al.* [35] present a stereo saliency modelthat leverages stereopsis, which provides depth cues and plays animportant role in the human vision system.Cropping-based thumbnail creation methods identify a rectangulararea encompassing attention-catching objects, which areusually determined by the saliency map. Suh *et al.* [1] integrateclassic saliency detection [24] with a greedy window searchalgorithm for automatic thumbnail cropping. A similar idea isalso 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 introducesa stereo saliency detection method by considering both saliencystimulus and stereopsis, which guarantees the consistency betweenthe 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. Thefirst step is a fast but effective likelihood estimation process,which calculates the probabilities of pixels belonging to fore-ground/background over entire dataset according to user scribbles.The estimated likelihood offers a rough estimation forforeground /background and is fed into next step as prior knowledge.In the secondstage, a higher-order energy based co-segmentation function isproposed to obtain final accurate co-segmentation results on agroup of images, which is based on higher order cliques. Our
higher-order cliques are constructed from a set of foregroundand background regions by user scribbles, where all the regionsin each image are matched to produce better co-segmentationperformance. Additionally, our approach considers the qualityof segmentation in higher-order energy to obtain more accurate estimations of foreground/background.

B. Likelihood Estimation

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

$$\begin{aligned} F_l^i &= F_1 + F_2 \\ &= \lambda^i \sum_{s=1}^{N(R^i)} (z_{s,l}^i - \varepsilon_{s,l}^i)^2 + \sum_{s,s'=1}^{N(R^i)} w_{s,s'}^i (z_{s,l}^i - z_{s',l}^i)^2 \end{aligned}$$

where the first term $F1$ defines an unary constraint that eachregion tends to have the initial likelihood $\varepsilon is,l$ estimated through the appearance similarity to foreground/background. The second term $F2$ gives the interactive constraint that all regions ofthe 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 estimatefor foreground/background in each image. For generatingmore accurate co-segmentation results, we further propose ahigher-order energy based co-segmentation function.In order to simultaneously segment a group of input images
$\{I^1, \dots \dots \dots I^n\}$with the labeled images T, we first build a globalterm Eglobal$\{I^1, \dots \dots \dots I^n,\ T\}$ to match all the images with thelabeled images T. The proposed energy of our co-segmentation
algorithm is expressed as follows:

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

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

The scalars ϵweight various terms.The unary termE_{unary}^{i} and the pairwise term $E_{pairwise}^{i}$ forimage $I^i$are defined as follows:

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

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

our co-segmentation energyfunction is given by,

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

D. Stereo Saliency Detection

In this section, we present the first half of our thumbnail generationsystem, the stereo saliency detection step, which aims at identifying the most important regions from input stereo imagepairs. 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 byany stereo algorithm such as the one in [38], [39]. The output ofour saliency algorithm is a pair of corresponding stereo saliencymaps *{SL; SR}*, where the intensity of each pixel represents theprobability 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 disparityboundaries are able to reveal the location of occlusion boundaries,which very often correspond to physical object boundaries. Thisphenomenon can be easily observed. Edges anddisparity boundaries provide complementary information. Edgesprecisely outline object contours. However, they are often toodense and appear inside objects as well. On the contrary, disparityboundaries typically do not cover entire object boundaries dueto errors in disparity estimation, but are relatively sparse andable to omit unnecessary details. These observations motivate usto integrate these two types of cues together for stereo saliencydetection.For a stereo image *Ik*(*k*ϵ*{L;R}*), we first compute an edge response *Ek*(x) for pixel x. The value of *Ek*(x) is normalized to[0, 1] with a higher value representing a higher probability of thepresence of an object boundary at pixel x. The edge probability map *Ek*is found using the edge detection technique , whichhas shown good performance in object contour detection. The edge response map *Ek* and disparity map *D* are integrated intoa disparity-edge map b *Ek* as follows:

$$\widehat{E}_k = \phi\left(E_{k}.\left(\lambda + \phi(\nabla D)\right)\right)$$

where∇D represents the gradient magnitude of the disparity map$D$ and ϕ (.) denotes the dilation operation with the radius typicallyset to 5 pixels. There usually exist discontinuities in disparity along object boundaries. Therefore, ideally, the gradient of disparityshould have a large magnitude around object boundaries. Inpractice, a locally maximal gradient magnitude may not coincideexactly with an object boundary due to approximations in disparitycalculation. We dilate disparity gradients and set the

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value of λ assmall as 0.2. The result is a sparse disparity-edge map $\hat{E}_k$, wherelocal 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.

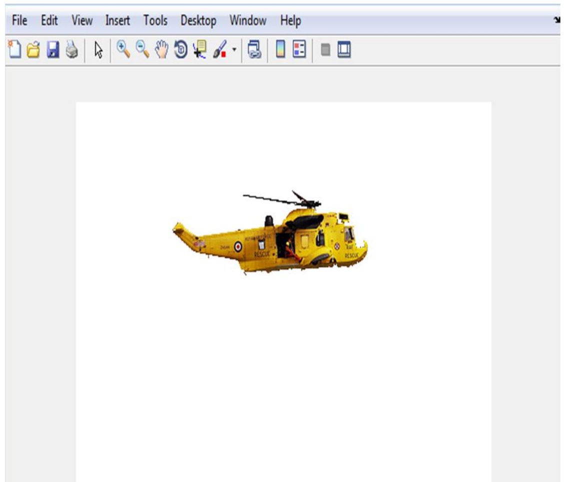

Fig 1.Input Image.

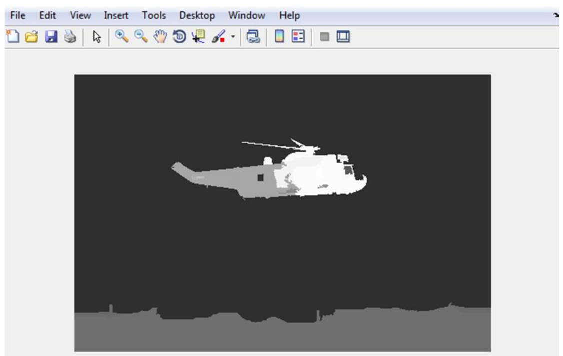

Fig 2. Co-Segment image

Fig 3. Saliency Segmentation

V. CONCLUSION

We have presented a novel interactive co-segmentation approachusing the likelihood estimation and high-order energyoptimization to extract the complicated foreground objects froma group of related images. A likelihood estimation method isdeveloped to compute the prior knowledge for our higher-orderco-segmentation energy function. Our higher-order cliques arebuilt on a set of foreground and background regions obtained bylikelihood estimation. Then our co-segmentation process froma group of images is performed at the region level through ourhigher-order cliques energy optimization. The energy functionof 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 theperformance of the stereo saliency detection algorithm Our experiments and user studies have demonstratedthatthe proposed stereo saliency detection algorithm is ableto produce more accurate results than co-segmentation results.

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