International Journal for Innovative Engineering and Management Research

A Peer Revieved Open Access International Journal

www.ijiemr.org

IJIEMR Transactions, online available on 7th Dec2017.Link :http://www.ijiemr.org/downloads.php?vol=Volume-6&issue=ISSUE-12

Title: **EFFICIENT CO-SEGMENTATION OF IMAGE USING HIGHER ORDER**

Volume 06, Issue 12, Pages: 178–182.

Paper Authors

NADIPOLLA MAHENDER,Mrs A MAMATHA,Mrs P PRASANNA KUMARI

DVR College of Engineering and Technology, Near IIT – HYD Permanent Campus, Ahead Of Patancheru, Kandi, Kashipur Village, Hyderabad, Telangana 502285

USE THIS BARCODE TO ACCESS YOUR ONLINE PAPER

International Journal for Innovative Engineering and Management Research
A Peer Revieved Open Access International Journal
www.ijiemr.org

EFFICIENT CO-SEGMENTATION OF IMAGE USING HIGHER ORDER

NADIPOLLA MAHENDER,**Mrs A MAMATHA,Mrs P PRASANNA KUMARI**

[1]Pg Scholar,Department of ECE, DVR College of Engineering and Technology, Near IIT – HYD Permanent Campus, Ahead Of Patancheru, Kandi, Kashipur Village, Hyderabad, Telangana 502285

[2]Asst.Prof, Department of ECE, DVR College of Engineering and Technology, Near IIT – HYD Permanent Campus, Ahead Of Patancheru, Kandi, Kashipur Village, Hyderabad, Telangana 502285

[2]Asst.Prof, HOD,Department of ECE, DVR College of Engineering and Technology, Near IIT – HYD Permanent Campus, Ahead Of Patancheru, Kandi, Kashipur Village, Hyderabad, Telangana 502285

ABSTRACT A new interactive image co segmentation algorithm using possibility estimation and higher order energy is proposed for extracting general foreground objects from a group of interrelated images. Our approach introduces the higher order cliques, energy into the co segmentation optimization process successfully. A region based likelihood estimation procedure is first performed to provide the primary knowledge for our higher order energy function. A new co segmentation energy function using higher order clique is developed, which can capably co segmentation energy function using higher order clique is developed, which can efficiently co segment the foreground objects with huge manifestation variations from a group of images in complex scenes. Both the quantitative and qualitative experimental results on representative datasets reveal that the accuracy of our co segmentation results is much higher than the stateof-the-art co segmentation methods.

Index Terms: Energy optimization, higher order cliques, image co segmentation, and likelihood estimation.

1. INTRODUCTION

IMAGE co-segmentation is commonly referred as jointly par- titioning multiple images into foreground and background components. The idea of cosegmentation is first introduced by Rother et al. [5] where they simultaneously segment common foreground objects from a pair of images. The cosegmentation problem has attracted much attention in the last decade, most of the co-segmentation approaches 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

International Journal for Innovative Engineering and Management Research
A Peer Revieved Open Access International Journal
www.ijiemr.org

optimization problems in multimedia processing. Similar rationale is also adopted by some co-saliency methods [9], [42], [44]. The existing image co-segmentation methods can be roughly classified into two main categories, including unsupervised co segmentation techniques and interactive co-segmentation approaches. The common idea of the unsupervised techniques [5], [11], [16], [22], [27], [29], [35], [37] formulates image co segmentation as an energy minimization and binary labeling problem. These approaches usually define the energy function using standard MRF terms and histogram matching term. The former encourages the consistent segmentations in every single image while the later penalizes the differences between the foreground histograms of multiple images. Inspired by interactive single-image segmentation methods [7], [15], [26], several interactive co-segmentation approaches [17], [19], [21], [28] using user scribbles have been proposed in recent years. The user usually indicates scribbles of foreground or background as additional constraint information to improve the co-segmentation performance. These interactive co segmentation approaches can handle a group of related images and improve the co-segmentation results by user scribbles. Batra et al. [19], [21] proposed an interactive image co-segmentation approach tosegment foreground objects with user interactions. They learned foreground/background appearance models using user scribbles. Recently, Collins et al. [28] formulated the interactive image cosegmentation problem as the random walk model and added the consistency constraint between the extracted objects from a set of input images. Their method utilized the normalized graph Laplacian matrix and solved the random walk optimization scheme by exploiting its quasi-convexity of foreground objects.

Higher Order Cliques A class of higher order clique potentials and show that the expansion and swap moves for any energy function composed of these potentials can be found by minimizing a sub modular function. We also show that for a subset of these potentials, the optimal move can be found by solving a st-mincut problem. We refer to this subset as the Pn Potts model.

Image Co-Segmentation Co-segmentation is the problem of simultaneously dividing q images into regions (segments) corresponding to k different classes. When q = 1 and k = 2, this reduces to the classical segmentation problem where an image is divided into foreground and background regions. Despite over 40 years of research, it is probably fair to say that there is still no reliable purely bottom-up single-image segmentation algorithm [9, 17, 22]. The situation is different when a priori information is available, for example in a supervised or interactive setting where labeled samples are available for the foreground and background (or even additional, k > 2) classes (see, e.g., [5, 6, 12]). The idea of co-segmentation is that the availability of multiple images that contain instances of the same “objects” classes makes up for the absence of detailed supervisory information.

International Journal for Innovative Engineering and Management Research
A Peer Revieved Open Access International Journal
www.ijiemr.org

Pn Potts Model We now introduce the Pn Potts model family of higher order clique potentials. This family is a strict generalization of the Generalized Potts model [4] and can be used for modeling many problems in Computer Vision. We define the Pn Potts model potential for cliques of size n as

$$\psi_c(x_c)= \begin{cases}\gamma_k & if \;\; x_i = l_k, \forall_i \in c \\ \gamma_{max} & otherwise\end{cases}$$

Where γmax>γk, ∀lk∈ L. For a pair wise clique this reduces to the P2 Potts model potential defined as ψij(a, b) = γk if a = b = lk and γmax otherwise. If we use γk = 0, for all lk, this function becomes an example of a metric potential function. Most energy minimization based methods for solving Computer Vision problems assume that the energy can be represented in terms of unary and pair wise clique potentials. This assumption severely restricts the representational power of these models making them unable to capture the rich statistics of natural scenes. Higher order clique potentials have the capability to model complex interactions of random variables and thus could overcome this problem. Researchers have long recognized this fact and have used higher order models to improve the expressive power of MRFs and CRFs [15, 19, 20]. The initial work in this regard has been quite promising and higher order cliques have been shown to improve results. However their use has been quite limited due to the lack of efficient algorithms for minimizing the resulting energy functions.

2. Our 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 fore-ground/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. This process is described in Section II-B. 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 ofsegmentation in higher-order energy to obtain more accurate estimations of foreground/background

B. Likelihood Estimation Given a group of images and the user scribbles that indicate foreground or background objects, we first compute pixel likelihood for foreground/background in imageThe likelihood of pixel is denoted by where l is a label indicating foreground (1) or background (0) and k is the index value of We compute the likelihoods of regions instead of pixels for computational efficiency. Each input image of the group is divided into regions using the oversegmentation methods such as mean shift [1] or efficient graph [6] method. For

International Journal for Innovative Engineering and Management Research
A Peer Revieved Open Access International Journal
www.ijiemr.org

each region, the region likelihoods of foreground and background are defined as, which is further formulated in a quadratic energy function as follows:

$$F_l^l = F_1 + F_2$$

$$= \kappa^l \sum_{s=1}^{N(R^l)} \left(z_{s,l}^l - \in_{s,l}^l\right)^2 + \sum_{s,s'=1}^{N(R^l)} \omega_{s,s'}^l \left(z_{s,l}^l - z_{s',l}^l\right)^2 \dots\dots\dots\dots 1$$

Where the first term defines a unary constraint that each region tends to have the initial likelihood estimated through the appearance similarity to foreground/background. The second term gives the interactive constraint that all regions of the whole image should have same likelihood when their representative colors are similar.

OBJECTIVE:

Compared to existing image co-segmentation methods, the proposed approach offers the following contributions.

1) We formulate the interactive image co-segmentation via likelihood estimation and high-order energy optimization, which utilizes the region likelihoods of multiple images and considers the quality of segmentation to achieve promising co-segmentation performance.

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

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

PROPOSED SCHEME:

The co-segmentation model is intuitive. Next we discuss how to design the global energy item in the following paragraphs. Previous co-segmentation approaches performed co-segmentation on image pairs and made simple assumption that two input images shared a same/similar foreground object. In contrast, we try to extract common foreground objects that have large variations in color, texture and shape from a group of images with complex background. Rather than building a simple foreground or background appearance model, we collect a region set of foreground/background according to user interaction.

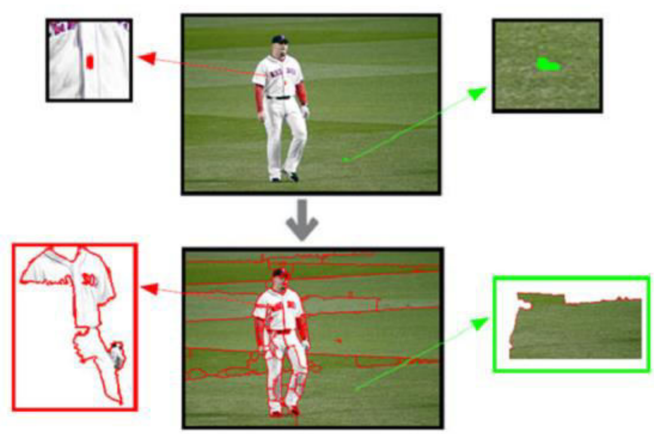

Fig. 1. Illustration of obtaining the region set from user seeds. In the top row, the middle image is one of the labeled images T. The scribble seeds are shown in close-ups, where the red (green) seeds denote the foregrounds (backgrounds). In the bottom row, the middle image denotes the over-segmentation results. Close-ups represent the labeled

regions U l which are extracted from these over-segmentations according to user seeds.

CONCLUSION We have presented a novel interactive cosegmentation 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 secondorder Boolean function and thus the traditional graph cuts method can be used to solve them exactly. The experimental results demonstrated both qualitatively and quantitatively that our method has achieved more accurate co segmentation results than previous unsupervised and interactive co-segmentation methods, even though the foreground and background have many overlap regions in color distributions or in very complex scenes.

REFERENCES

[1] P. Loizou, Speech Enhancement Theory and Practice. Boca Raton, FL, USA: CRC Press, 2007.

[2] S. Srinivasan, J. Samuelsson, and W. B. Kleijn, “Codebook-based Bayesian speech enhancement for nonstationary environments,” IEEE Trans. Audio, Speech Lang. Process., vol. 15, pp. 441–452, Feb. 2007.

[3] R. C. Hendriks, T. Gerkmann, and J. Jensen, DFT-Domain based single-microphone noise reduction for speech enhancement-a Survey of the State of the Art. San Rafael, CA, USA: Morgan & Claypool, 2013.

[4] V. Grancharov, J. H. Plasberg, J. Samuelsson, and W. B. Kleijn, “Generalized post filter for speech quality enhancement,” IEEE Trans. Audio, Speech Lang. Process., vol. 16, no. 1, pp. 57–64, Jan. 2008.

[5] R. Niederjohn and J. Grotelueschen, “The enhancement of speech intelligibility in high noise levels by high-pass filtering followed by rapid amplitude compression,” IEEE Trans. Acoust.Speech, Signal Process., vol. ASSP-24, no. 4, pp. 277–282, 1976.