Image Segmentation Using Hybrid Approach of Pairwise Constraints Propagation and Correlation Clustering

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Abstract- *Image segmentation is the process of partitioning a digital image into multiple segments which plays an important role in applications of computer vision, objects recognition, object tracking and image analysis. There are a large number of methods present that can extract the required foreground from the background.*

Proposed work aims to partition an image which uses an interactive information. Interactive image segmentation technique is based on adaptive constraints propagation (ACP). This system is known as ACP Cut. Input provided by user is very important factor to improve the effectiveness of system. Initially in proposed work superpixels are generated for a complete pixel based image by using the Simple Linear Iterative Clustering (SLIC) method. These superpixels are used to extract color based features which are further used to derive pairwise constraints. These pair-wised constraints are further used by ACP seed propagation method to differentiate foreground object from background portion of an given input image. Additionally, Segmentation method based on clustering contributes in foreground extraction which aims to improve the time efficiency and accuracy of image segmentation.

Keywords- Superpixels, Adaptive constraint propagation, seed propagation, interactive image segmentation.

I. INTRODUCTION

The significant advances in imaging devices and tech- nologies, digital images play a more imperative part in our life. A images records a scene of this present reality in a numeric representation which will be stored, transmitted and contemplated thereafter. The outstanding precept “a picture is worth a thousand words” demonstrates that a picture has an effective capacity of portraying the rich data it carries. Image processing is the use of computer algorithms to perform image processing on digital images. As a subcategory or field of digital signal processing, digital image processing has many advantages over analog image processing. It allows a much wider range of algorithms to be applied to the input data and can avoid problems such as the build-up of noise and signal distortion during processing. Since images are defined over two dimensions (perhaps more) digital image processing may be modeled in the form of multidimensional systems. Image processing image processing has become the most common form of image processing and generally, is used because it is not only the most versatile method, but also the cheapest. In computer vision;pictures are utilized to perform perception tasks, for example, object detection, classification, feature extraction, multi-scale signal analysis, pattern recognition, projection among others.

Image segmentation is the task in which the image is divided in multiple components in such a way that the each part/component has some significance. As an image is consist of various pixels the segmentation issue can be taken as a labeling issue that concentrates on assigning a label to every pixel showing a specific component in the scene. Alternatively retrieving boundaries in various objects can be named as segmentation so that the image is divided in meaningful areas with respect to the boundaries. When the segmentation of given image is performed, it not only enables the computer to know about the image composition, but also enables the computer to analyze the qualitative and quantitative properties of the object of interest based on its segmented region in the image.

In proposed system dataset of images is taken as an input and pixel generation is performed on the dataset. Superpixels are generated for a complete pixel based image by using the Simple Linear Iterative Clustering (SLIC) method. After that generate feature extraction and pairwise constraints by mean shift segmentation. GDIS segmentation is used for the correlation clustering of same color histograms and after seed propagation foreground image segmentation is performed.

In this paper we study about the related work done, in section II, the proposed approach modules description, mathematical modeling, algorithm and experimental setup in section III .and at final we provide a conclusion in section IV.

II. REVIEW OF LITERATURE

In paper [1], authors apply efficient implementations of integer linear programming to the problem of image segmentation. The image is first grouped into superpixels and then local information is extracted for each pair of spatially adjacent superpixels. Given local scores on a map of several hundred superpixels, use correlation clustering to find the global segmentation that is most consistent with the local evidence. Probabilistic modeling of image segmentation based on correlation clustering and an efficient algorithm of the ILP optimization problem.

In paper [2], authors 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 prior knowledge for our higher order energy function. Then, a new co-segmentation energy function using higher order cliques is developed, which can efficiently co-segment the foreground objects with large appearance variations from a group of images in complex scenes.

In paper [3], authors uses supervised hierarchical approach to object-independent image segmentation. Starting with over- segmenting superpixels, we use a tree structure to represent the hierarchy of region merging, by which we reduce the problem of segmenting image regions to finding a set of label assignment to tree nodes. Formulate the tree structure as a con- strained conditional model to associate region merging with likelihoods predicted using an ensemble boundary classifier. Final segmentations can then be inferred by finding globally optimal solutions to the model efficiently.

In paper [4], authors presents an unsupervised and semi- automatic image segmentation approach where formulate the segmentation as an inference problem based on unary and pairwise assignment probabilities computed using low-level image cues. The inference is solved via a probabilistic graph matching scheme, which allows rigorous incorporation of low- level image cues and automatic tuning of parameters. The pro- posed scheme is experimentally shown to compare favorably with contemporary semi-supervised and unsupervised image segmentation schemes, when applied to contemporary state- of-the-art image sets.

In paper [5] authors presents semantic image segmentation is a fundamental yet challenging problem, which can be viewed as an extension of the conventional object detection with close relation to image segmentation and classification. It aims to partition images into non-overlapping regions that are assigned predefined semantic labels. Most of the existing approaches utilize and integrate low level local features and high-level contextual cues, which are fed into an inference framework such as, the conditional random field (CRF). It proposes an ontology based semantic image segmentation (OBSIS) approach that jointly models image segmentation and object detection. Dirichlet process mixture model transforms the low-level visual space into an intermediate semantic space, which drastically reduces the feature dimensionality. These features are then individually weighed and independently learned within the context, using multiple CRFs.

In paper [6],Image segmentation aims to separate the desired foreground object from the background. Since color and texture in natural images are very complex, automatic segmentation of foreground objects from the complex background meets a significant obstacle when foreground and background have similar features.Interactive image segmentation using adaptive constraint propagation (ACP), called ACP Cut. In interactive image segmentation, the interactive inputs provided by users play an important role in guiding image segmentation. However, these simple inputs often cause bias which leads to failure in preserving object boundaries.

In paper [7] author propose the eigenvalue problem of an anisotropic diffusion operator for image segmentation. The diffusion matrix is defined based on the input image. The eigen functions and the projection of the input image in some eigen space capture key features of the input image. An important property of the model is that for many input images, the first few eigen functions are close to being piecewise constant, which makes them useful as the basis for a variety of applications, such as image segmentation and edge detection. The eigenvalue problem is shown to be related to the algebraic eigenvalue problems resulting from several commonly used discrete spectral clustering models. The relation provides a better understanding and helps developing more efficient numerical implementation and rigorous numerical analysis for discrete spectral segmentation methods. The new continuous model is also different from energy-minimization methods such as active contour models in that no initial guess is required for in the current model.

In paper [8] authors at developing an integrated system for clothing co-parsing, in order to jointly parse a set of clothing images (unsegmented but annotated with tags) into semantic configurations. A novel data-driven system consisting of two phases of inference is proposed. The first phase, referred as image co-segmentation, iterates to extract consistent regions on images and jointly refines the regions over all images by employing the exemplar-SVM technique. In the second phase (i.e., region co-labeling), construct a multiimage graphical model by taking the segmented regions as vertices, and incor- porating several contexts of clothing configuration (e.g., item locations and mutual interactions). The joint label assignment can be solved using the efficient Graph Cuts algorithm.

In paper [9] authors proposes a novel automatic reference color selection (ARCS) scheme for the adaptive mathematical morphology (MM) method, and is specifically designed for color image segmentation applications. Because of the main advantages of being intuitive and simple, in the past decade, it has contributed to the growing popularity of binary and gray-scale MM processing. However, the MM process typ- ically neglects the details of reference color determination. Applying other ordering methods, which select only black as the reference color for sorting pixels, result in the problem in which the scope of the distance measurement is not optimal. The proposed ARCS scheme is used for determining the ideal reference color for MM and for color image segmentation application.

In paper [10] authors propose to exploit inter-image in- formation through cosaliency, and then perform single-image segmentation on each individual image. To make the system robust and to avoid heavy dependence on one single saliency extraction method, apply multiple existing saliency extraction methods on each image to obtain diverse salient maps. Ma- jor contribution lies in the proposed method that fuses the obtained diverse saliency maps by exploiting the inter-image information, which known as saliency co-fusion.

In paper [11], authors developed an interactive image segmentation technique from a new perspective of cascaded metric learning. By utilizing the data acquired by cascaded metric learning, designed technique proceeds with learning the optimal metric based on view of current labeled samples, and relegating the unlabeled samples to labeled set with the high certainty basing on current classification results.

In paper [12] authors have presented an interactive segmen- tation technique depending on the semi-supervised learning technique commonly named as particle competition and coop- eration. In designed method particles walk in a graph created from the image which is to be segmented. Particles repressing the object relate with other particles to dominate the unlabeled pixels, when the particles pointing to the other object compete with every other for avoiding invasion from enemy particles in the nodes they already dominated. Pixels which are labeled with low confidence by the particle competition as well as cooperation technique pass through a second phase and then offering from their adjacent pixels in the original image, in order to get their definitive label.

In paper [13] authors developed a system known as MILCut, which is a sweeping line multiple instance learning paradigm to segment the object present in foreground in a bounding box given by user. Authors theoretically justified that the sweeping line method for MIL bagging naturally grabs the user's intention carried by a bounding box. The designed algorithm is simple, easy to implement, and provides accuracy and efficiency.

In paper [14] authors given a comparison of some literature on color image segmentation based on region growing and merging algorithm. At the end an automatic seeded region growing algorithm is developed for segmenting color images. The implemented method is interactive because it makes use of different threshold values for region merging as well as for region growing.

In paper [15] authors proposes an efficient agglomerative algorithm based on modularity optimization. Given an over- segmented image that consists of many small regions, al- gorithm automatically merges those neighboring regions that produce the largest increase in modularity index. When the modularity of the segmented image is maximized, the algo- rithm stops merging and produces the final segmented image. To preserve the repetitive patterns in a homogeneous region, a feature based on the histogram of states of image gradients, and use it together with the color feature to characterize the similarity of two regions. By constructing the similarity matrix in an adaptive manner, the over-segmentation problem can be effectively avoided.

III. SYSTEM ARCHITECTURE / SYSTEM OVERVIEW

A. Proposed System Overview

In propose system ACP Cut to propagate characteristics of the user's interactive information into the whole image successfully while maintaining global data coherence, as well as learn a global image discriminative structure for interactive image segmentation. ACP Cut adopts adaptive constraints instead of traditional hard constraints to learn a global dis- criminative structure. In previous work, system have provided the original ACP formulation for semisupervised kernel ma- trix learning (SS-KML). However, it has high computational complexity because its computational cost rises very rapidly as the number of samples is increased. Thus, it is not suitable for practical applications which need fast processing. To deal with this problem, we employ seed propagation in the ACP learning procedure to remarkably improve the computational complexity of ACP.We apply ACP with seed propagation to interactive image segmentation, called ACP Cut, and verify its effectiveness and efficiency in image segmentation. Initially in proposed work superpixels are generated for a complete pixel based image by using the Simple Linear Iterative Clus- tering (SLIC) method. Then, system extract features from superpixels obtained by mean-shift segmentation in an image. Then, system generate pairwise constraints from the user's interactive information. Next, system perform ACP with seed propagation on both features and pairwise constraints to learn a global discriminative structure in an image. Finally, system assign a label of foreground/background to each superpixel based on the learned discriminative structure, thus segmenting foreground objects from background.

In proposed system, ACP cut is improved with segmentation method for foreground image segmentation, which improves the time efficiency and accuracy of image segmentation out- put. Experimental result will prove that the proposed system outperforms the ACP Cut meth of for improved image seg- mentation in terms of accuracy and speed.

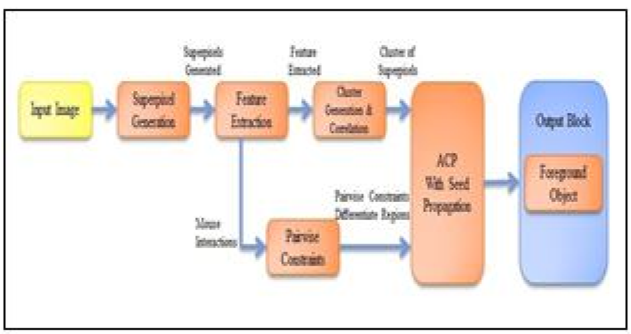


Figure 1. System Architecture

B. Algorithm 1: SLIC Super pixel Algorithm

Input: Input Image

Output: Image with superpixels.

1) Read the input image pixel by pixel. Let I is set of input images.
   I = {I1, I2, ..., In}I is Input Image, n is No. of Image
2) RGB value of every pixel and store the Red, Green and Blue color value into respective list.
   In = {P1, P2, ..., Pn} P is 24 bit color pixel
   Col is set of 3 color planes RGB Col={Cr, Cg, Cb}
   Cr = {Cr1, Cr2, ..., Crn}Crn represents red color value of ith pixel
   Cg = {Cg1, Cg2, ..., Cgn}Cgn represents green color value of ith pixel
   Cb = {Cb1, Cb2, ..., Cbn}Cbn represents blue color value of ith pixel
3) Cell width of image contains all pixels as N and Prox- imity K by this we get size of superpixels is N/K.
4) Traverse image by row by row collect the pixel which approximate same according to threshold of pixel value. Store position of pixels in array.
5) Generate one array for the Distance between pixel and other array for labeling center of superpixels.
6) Merge pixel to create superpixel which have same RGB value and assign label center for highest value. Is =
   {S1, S2, ..., Sn}S represents center of the superpixel
   Create output image with superpixels.

C. Algorithm 2: Clustering Algorithm

Input: Image with superpixels;

Output: Image with containig clusters.

1) Get image with superpixels as input.
   Is = {S1, S2, ..., Sn}S represents center of the super- pixels
2) Traverse the array containing centers of superpixels.
3) Insert the center of superpixels in a list with respect to RGB value shows affinity between them.
   C1= {K1, K2, ..., Kn} Where C1 represents Cluster contains K suerpixels with specified color affinity value of RGB.
   C2= {J1, J2, ..., Jn}Where C2 represents Cluster contains J suerpixels with specified color affinity value of RGB
   Cn= {L1, L2, ..., Ln}Where Cn represents Cluster contains L suerpixels with specified color affinity value of RGB
4) Merge the same color superpixels to get clusters of it.
5) Output provides the cluster image of superpixels.

D. Algorithm 3: Mouse Interaction Algorithm

Input: Image with cluster segmentation

Output: Red Line dragged by Mouse

1) Take clustered image as input.
   C = {C1, C2, ..., Cn}C represents all Cluster.
2) Select the region which we want to extract foreground object .
3) Using mouse interaction include the cluster will be selected in foreground object.
4) Store the x,y co-ordinate of dragged pixels added to list.
5) Compare mouse dragged point position with cluster pixel points. If point match then select whole cluster.
   Foreground contains clusters included knows as Must-link.
   M = {ML1, ML2, ..., MLn} ML is Must-Link
6) Constraints, n is No. of Constraints
7) Remaining cluster in image termed as Connot-link.
   N = {NL1, NL2, ..., NLn} NL is Cannot-Link Constraints, n is No. of Constraints

E. Algorithm 4: ACP Cut Algorithm

Input: Cluster Image

Output: Image with Foreground Object

1) In this module we use two sets C clusters and M Must-Link.
2) Select entry from Must-link set.
3) Fetch clusters associated with Must-Link entry as per foreground image.
4) Repeat Step 2 and 3 for all entries of Must-Link.

IV. MATHEMATICAL MODEL

S = { I, f(x),O}
I = Input image
F(x) = Set of Function
F(x) = {Sup gen, Clusters, Mouse Inter,ACP cut}
I = {I1, I2, ..., In}
'I' is Input Image 'n' is No. of Image

Is = Sup gen(I)
Is = {S1, S2, ..., Sn}
'Is' is Superpixel
'n' is No. of Superpixel

C = Clusters(Is)
C1= {K1, K2, ..., Kn}
C2= {J1, J2, ..., Jn}
Cn= {L1, L2, ..., Ln}
C is Clusters of superpixles n is No. of Clusters

E = Mouse Inter(C)
M ={ML1, ML2, ..., MLn}
L is Must-Link Constraint n is No. of Constraints
N = {NL1, NL2, ..., NLn}
NL is Cannot-Link Constraints n is No. of Constraints

Fg, Bg = ACP cut ({E})
Fg= {ML1, ML2, ..., MLn}

L is Must-Link Constraints

Bg= {NL1, NL2, ..., NLn}
NL is Cannot-Link Constraints.

O = Output O = {Fg}
O = Represent the Foreground segmentation.

V. RESULTS AND DISCUSSION

A. Experimental Setup

The system is built using Java framework on Windows platform. The Net beans IDE is used as a development tool. The system doesn't require any specific hardware to run; any standard machine is capable of running the application. For image segmentation processing Berkeley segmentation (BSD500)dataset is use. Size of 230 MB which contains 200 test image, 200 train images , 100 validation images and ground- truth values.

B. Evaluation Parameters and Results

For the evaluation parameters use results for tests that detect the presence of a condition (a test result is either positive or negative, which may be true or false).
True Positive (TP) test result is one that detects the condition when the condition is present. Means Pixels correctly segmented as foreground.

True Negative (TN) test result is one that does not detect the condition when the condition is absent. Means Pixels falsely segmented as foreground.

False Positive (FP) test result is one that detects the condition when the condition is absent. Means Pixels correctly seg- mented as background.

False Negative (FN) test result is one that does not detect the condition when the condition is present. Means Pixels falsely segmented as background.

In this framework first gets the optimal boundary matching between the testing segmentation and the ground-truth, and then evaluates the results from two aspects: Precision and Recall.

The Precision measures the fraction of detected boundary pixels that match the ground-truth boundaries,and is defined as:

$$\text{Precision} = \frac{TP}{TP+FP}$$

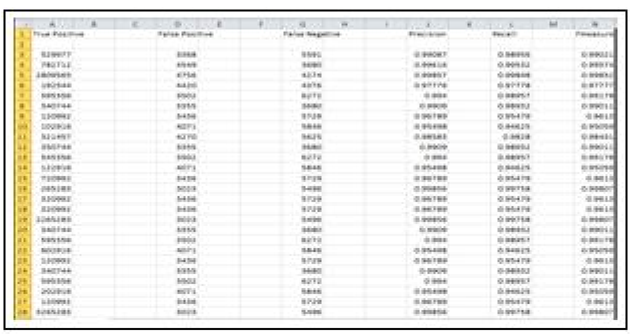
Similarly, the Recall is defined as: $\text{Rec all} = \frac{TP}{TP+FN}$.

which measures the fraction of ground-truth boundary pixels that are detected. To summarize these two indices, the global F -measure, is used to measure the harmonic mean of the Precision and Recall.

$$F\text{-measure} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Recall}+\text{Precision}}$$

A = average of F-measure
n = the number of images.
xi = the F-measure of each individual image. Result is calculated on 260 Images.
A = average of F-measure on 260 images
n = the number of images 260.
xi = the F-measure of each individual image.

A = 0.97575

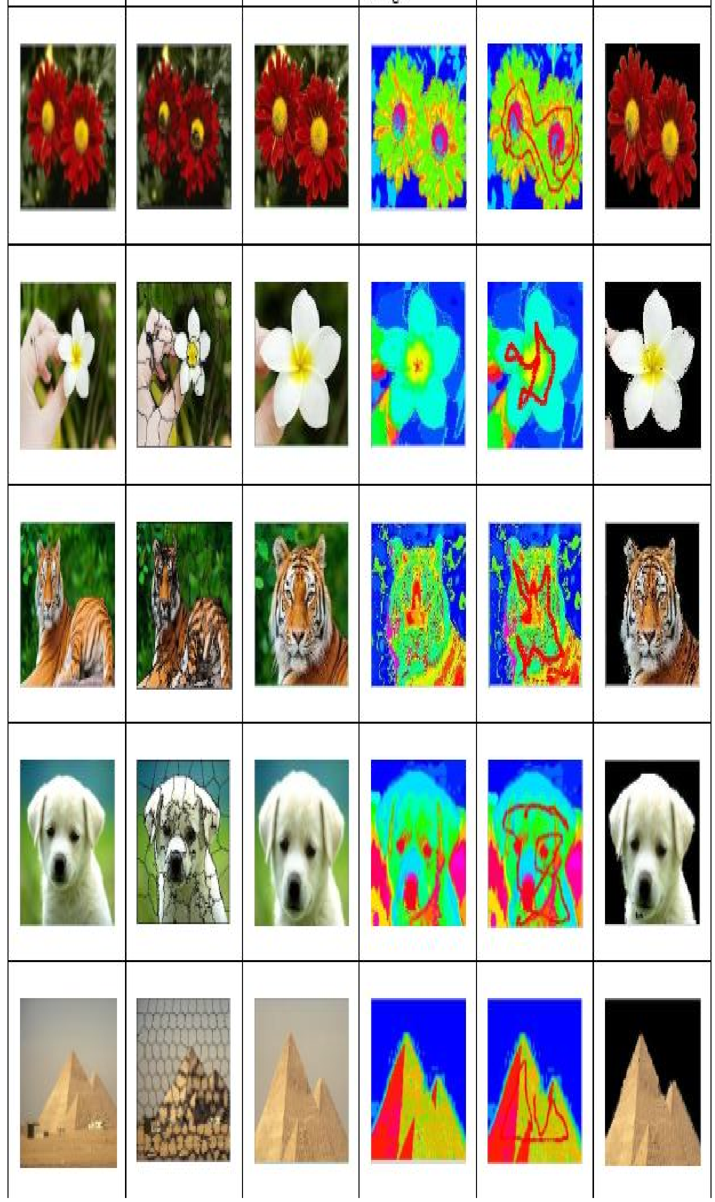


True Positive	False Positive	False Negative	Precision	Recall	FMeasure

Figure 2. Result Table

Table 1. STAGES OF FOREGROUND EXTRACTION

Input Image	Superpixel Image	Selected Image	Clustered Segmentated Image	Mouse Interaction	Foreground Image



VI. CONCLUSION

Image segmentation process introduced ACP Cut based on adaptive constraints for interactive image segmentation. In this implementation consider the two features based on color clusters and the pairwise constraints as Must-link and Cannot- Link for foreground extraction by using ACP cut method. In this RGB values of pixels consider for the differentiate the foreground regions from the image. It auto detect the boundary region of the selected foreground image for the extraction of the image. Proposed method gives accuracy as 0.97575 for foreground object as a result. ACP cut enhances the good discrimination of foreground by Constraints and mouse interactions and achieves good segmentation results.

REFERENCES

[1] Amir Alush and Jacob Goldberger, ”Hierarchical Image Segmentation Using Correlation Clustering,” IEEE transactions on neural networks and learning systems, vol. 27, no. 6, June 2016

[2] Wenguan Wang and Jianbing Shen, ”Higher-Order Image Co- segmentation,” IEEE transactions on multimedia, vol. 18, no. 6, June 2016.

[3] Ting Liu, Mojtaba Seyedhosseini, and Tolga Tasdizen, ”Image Seg- mentation Using Hierarchical Merge Tree,” IEEE transactions on image processing, vol. 25, no. 10, October 2016.

[4] Ayelet Heimowitz and Yosi Keller, ”Image Segmentation via Probabilistic Graph Matching,” IEEE transactions on image processing, vol. 25, no. 10, October 2016.

[5] Mohsen Zand, Shyamala Doraisamy, Alfian Abdul Halin, and Mas Rina Mustaffa, ”Ontology-Based Semantic Image Segmentation Using Mixture Models and Multiple CRFs,” IEEE transactions on image processing, vol. 25, no. 7, July 2016.

[6] Meng Jian and Cheolkon Jung, ”Interactive Image Segmentation Using Adaptive Constraint Propagation,” IEEE transactions on image process- ing

[7] Jingyue Wang and Weizhang Huang, ”Image Segmentation With Eigen- functions of an Anisotropic Diffusion Operator,” IEEE transactions on image processing, vol. 25, no. 5, may 2016.

[8] Xiaodan Liang, Liang Lin, Wei Yang, Ping Luo, Junshi Huang, and Shuicheng Yan ”Clothes Co-Parsing Via Joint Image Segmentation and Labeling With Application to Clothing Retrieval,” IEEE transactions on multimedia, vol. 18, no. 6, june 2016.

[9] Huang-Chia Shih and En-Rui Liu, ”Automatic Reference Color Selec- tion for Adaptive Mathematical Morphology and Application in Image Segmentation,” IEEE transactions on image processing, vol. 25, no. 10, october 2016.

[10] Koteswar Rao Jerripothula, Jianfei Cai, and Junsong Yuan, ”Image Co- segmentation via Saliency Co-fusion,” IEEE ransactions on multimedia, vol. 18, no. 9, september 2016.

[11] W. Li, Y. Shi, W. Yang, H. Wang and Y. Gao, “Interactive image segmentation via cascaded metric learning,” 2015 IEEE International Conference on Image Processing (ICIP), Quebec City, QC, 2015, pp. 2900-2904.

[12] F. Breve, M. G. Quiles and L. Zhao, “Interactive image segmentation using particle competition and cooperation,” 2015 International Joint Conference on Neural Networks (IJCNN), Killarney, 2015, pp. 1-8.

[13] J. Wu, Y. Zhao, J. Y. Zhu, S. Luo and Z. Tu, “MILCut: A Sweeping Line Multiple Instance Learning Paradigm for Interactive Image Seg- mentation,” 2014 IEEE Conference on Computer Vision and Pattern Recognition, Columbus, OH, 2014, pp. 256-263.

[14] M. Mary Synthuja Jain Preetha, L. Padma Suresh and M. John Bosco, “Image segmentation using seeded region growing,” 2012 International Conference on Computing, Electronics and Electrical Technologies (IC- CEET), Kumaracoil, 2012, pp. 576-583.

[15] Shijie Li and Dapeng Wu, “Modularity Based Image Segmentation,” IEEE Transactions on Circuits and Systems for Video Technology 2014.

[16] W. Tao, H. Jin, and Y. Zhang, ”Color image segmentation based on mean shift and normalized cuts,” IEEE Transactions on Systems, Man, and Cybernetics- Part B: Cybernetics, vol. 37, no. 5, pp. 13821389, 2007.

[17] B. Peng, L. Zhang, and D. Zhang, ”Automatic image segmentation by dynamic region merging,” IEEE Transactions on Image Processing, vol.20, no. 12, pp. 35923605, 2011.

[18] R. Carsten, K. Vladimir, and B. Andrew, ”Grabcut: interactive fore- ground extraction using iterated graph cuts,” ACM Transactions on Graphics, vol. 23, no. 3, pp. 309314, 2004.

[19] J. Ning, L. Zhang, D. Zhang, and C. Wu, ”Interactive image segmen- tation by maximal similarity based region merging,”Pattern Recognition, vol. 43, no. 2, pp. 445456, 2010.

[20] S. Nowozin, C. Rother, S. Bagon, T. Sharp, B. Yao, and P. Kohli, ”Decision tree fields,” Proceedings of IEEE

Conference on Computer Vision, pp. 16681675, 2011.

[21] M. Mary Synthuja Jain Preetha, L. Padma Suresh and M. John Bosco, “Image segmentation using seeded region growing,” 2012 International Conference on Computing, Electronics and Electrical Technologies (IC- CEET), Kumaracoil, 2012, pp. 576-583.

[22] W. Lu, J. Oakley, D. Russakoff and R. Chang, “Vitreo-retinal inter- face segmentation from spectral-domain OCT using change detection and belief propagation,” 2013 IEEE 10th International Symposium on Biomedical Imaging, San Francisco, CA, 2013, pp. 1320-1323.

[23] Y. Taguchi, B. Wilburn and C. L. Zitnick, “Stereo reconstruction with mixed pixels using adaptive over-segmentation,” 2008 IEEE Conference on Computer Vision and Pattern Recognition, Anchorage, AK, 2008, pp. 1-8.

[24] W. Li, Y. Shi, W. Yang, H. Wang and Y. Gao, ”Interactive image segmentation via cascaded metric learning,” 2015 IEEE International Conference on Image Processing (ICIP), Quebec City, QC, 2015, pp. 2900-2904.

[25] F. Breve, M. G. Quiles and L. Zhao, “Interactive image segmentation using particle competition and cooperation,” 2015 International Joint Conference on Neural Networks (IJCNN), Killarney, 2015, pp. 1-8.

[26] J. Wu, Y. Zhao, J. Y. Zhu, S. Luo and Z. Tu, “MILCut: A Sweeping Line Multiple Instance Learning Paradigm for Interactive Image Seg- mentation,” 2014 IEEE Conference on Computer Vision and Pattern Recognition, Columbus, OH, 2014, pp. 256-263.

[27] L. A. C. Mansilla, M. P. Jackowski and P. A. V. Miranda, “Image foresting transform with geodesic star convexity for interactive image segmentation,” 2013 IEEE International Conference on Image Processing, Melbourne, VIC, 2013, pp. 4054-4058.

[28] Q. Sun and H. Tian, “Interactive image segmentation using power water- shed and active contour model,” 2012 3rd IEEE International Conference on Network Infrastructure and Digital Content, Beijing, 2012, pp. 401-405.