International Journal of Science and Research (IJSR)
ISSN (Online): 2319-7064
Index Copernicus Value (2013): 6.14 | Impact Factor (2015): 6.391

An Interactive Hybrid Image Segmentation Based on PCC and Region Approach

Amandeep Kaur[1], Rupika Rana[2]

[1]Department of Computer Science, SSIET, Punjab Technical University, Regional Centre, Derabassi, Punjab

[2]Assistant Professor, Department of Computer Science and Engineering, SSIET, Punjab Technical University, Regional Centre, Derabassi, Punjab

Abstract: ***Semi-supervised learning is applied to classification problems where only a small portion of the data items is labeled. In these cases, the reliability of the labels is a crucial factor, because mislabeled items may propagate wrong labels to a large portion or even the entire data set. In the interactive image segmentation problem, a human specialist labels some pixels of an object while the semi-supervised algorithm labels the remaining pixels of the segment. The particle competition and cooperation model is a recent graph-based semi-supervised learning approach. It employs particles walking in a graph to classify the data items corresponding to graph nodes. Each particle group aims to dominate most unlabeled nodes, spreading their label, and preventing enemy particles invasion. Region-based image segmentation is an important preprocessing step for high-level computer vision tasks. This is used to present an approach to image partition into regions that reflect the objects in a scene. In this paper an interactive hybrid image segmentation technique to be based on particle competition- cooperation and region based similarity is proposed. This technique has combined effect of particle and region based approach. The results are checked with parameters like error rate.***

Keywords: image segmentation, supervised learning, image partition, computer vision, graph

1. Introduction

Image segmentation is the process of dividing a digital image into multiple parts (sets of pixels), identifying objects or other relevant information [1]. Image segmentation is considered one of the most difficult tasks in image processing [2]. Furthermore, fully automatic segmentation is still a big challenge and the techniques are often domain-dependent. Therefore, interactive image segmentation, which takes a partial supervision into account, has emerged as an interesting approach in the last decades. Segmentation is typically associated with pattern recognition problems. It is considered the first phase of a pattern recognition process and is sometimes also referred to as object isolation. Many interactive image processing approaches are based on semi-supervised learning (SSL). SSL is an important paradigm in the machine learning field especially in problems where unlabeled data is abundant and labeled data is expensive and/or time consuming, requiring an intense work of human specialists [3], [4]. SSL techniques employ both labeled and unlabeled data in its training process, overcoming the limitations of both supervised and unsupervised learning approaches, which use only labeled or unlabeled data, respectively. In the interactive image segmentation problem, a human specialist could label some pixels far from the object borders, which is an easier and faster task than defining object boundaries manually. Thus, by taking the labeled and unlabeled pixels into account, the semi-supervised learning algorithm propagates the labels from the labeled pixels to their related remaining unlabeled pixels, or the image segments.

The particle competition and cooperation model [5] is a recent graph-based semi-supervised learning approach. Firstly, it converts vector-based data sets to non-weighted and undirected graphs, so each data item becomes a graph node, and edges are created between nodes corresponding to similar data items. Then, particles, which correspond to labeled data, walk in the graph in cooperation with other particles representing the same class and competing against particles representing other classes. Each particle group aims to dominate most unlabeled nodes, spreading their label, and preventing enemy particles invasion. At the end of the process, particles territory frontiers usually fall near the boundaries between classes, thus achieving high classification accuracy.

2. Literature Survey

F. Breve et al. [2015] The particle competition and cooperation model is a recent graph-based semi-supervised learning approach. It employs particles walking in a graph to classify the data items corresponding to graph nodes. Each particle group aims to dominate most unlabeled nodes, spreading their label, and preventing enemy particles invasion. In this paper, the particle competition and cooperation model is extended to perform interactive image segmentation. Roughly speaking, the semi-supervised learning particle competition and cooperation method [6] works as follows. Firstly, the vector-based data set is converted to a non-weighted and undirected graph. Each graph node represents a sample. Edges between a pair of nodes are created if the Euclidean distance between them is below a threshold. Alternatively, a k-nearest neighbors approach can be used to establish the edges. Secondly, a particle is created for each labeled node. Particles corresponding to nodes with the same label define a team and cooperate among themselves to dominate the unlabeled nodes. On the other hand, particles corresponding to nodes with different labels compete against each other for the possession of the nodes. Finally, as the system runs, the particles walk in the graph following a random-greedy rule

Licensed Under Creative Commons Attribution CC BY

[6]. The proposed method has showed foreground segmentation accuracy, which is comparable to those, achieved by some state-of-the-art methods, and even slightly better accuracy in some specific images.

A. Ducournau et al. [2014] introduced for the first time the notion of directed hypergraphs in image processing and particularly image segmentation. They give a formulation of a random walk in a directed hypergraph that serves as a basis to a semi-supervised image segmentation procedure that is configured as a machine learning problem, where a few sample pixels are used to estimate the labels of the unlabeled ones. They proposed a DINH (Directed Image Neighborhood Hypergraph) model as a directed hypergraph representation of the image content, and adapted it to a semi-supervised image segmentation problem using a transition matrix computed from our random walk formulation. Experiments on the standard Microsoft GrabCut datasets showed encouraging results in comparison with algorithms using undirected and directed graphs and undirected hypergraph-based image representation. In particular, results show that the introduction of directional information unto a hypergraph model can help at improving the segmentation results due to an asymmetric weighting of the hyperarcs.

F. Breve [2013] In this paper, those two machine learning techniques are combined into a single nature-inspired method. It features particles walking on a network built from the data set, using a unique randomgreedy rule to select neighbors to visit. The particles, which have both competitive and cooperative behavior, are created on the network as the result of label queries. They may be created as the algorithm executes and only nodes affected by the new particles have to be updated. Therefore, it saves execution time compared to traditional active learning frameworks, in which the learning algorithm has to be executed several times. The data items to be queried are select based on information extracted from the nodes and particles temporal dynamics. Two different rules for queries are explored in this paper, one of them is based on querying by uncertainty approaches and the other is based on data and labeled nodes distribution. Each of them may perform better than the other according to some data sets peculiarities. Rule A works better in data sets where the classes are well separated and there are not many outliers, because in these cases the dense regions are easily classified and the uncertainty is mostly in frontier regions. Rule B, on the other hand, usually works better when the classes are not well defined and/or there are outliers, because in these cases the labeled nodes are sparsely distributed. Experimental results on some real-world data sets are provided, and the proposed method outperforms the semi-supervised learning method, from which it is derived, in all of them.

F. Breve et al. [2012] this paper aims to address this problem by presenting a graph-based (network based) semi-supervised learning method, specifically designed to handle data sets with mislabeled samples. The method uses teams of walking particles, with competitive and cooperative behavior, for label propagation in the network constructed from the input data set. The proposed model is nature-inspired and it incorporates some features to make it robust to a considerable amount of mislabeled data items. Computer simulations show the performance of the method in the presence of different percentage of mislabeled data, in networks of different sizes and average node degree. Importantly, these simulations reveals the existence of the critical points of the mislabeled subset size, below which the network is free of wrong label contamination, but above which the mislabeled samples start to propagate their labels to the rest of the network. Moreover, numerical comparisons have been made among the proposed method and other representative graph-based semi-supervised learning methods using both artificial and real-world data sets. Interestingly, the proposed method has increasing better performance than the others as the percentage of mislabeled samples is getting larger.

Region based segmentation is another image segmentation method in which the image is divided into its constituent sub-divisions which has similar properties known as regions [13]. This segmentation can be categorized into various techniques.

3. Techniques for Implementation

In this research work, an interactive hybrid image segmentation technique to be based on particle competition-cooperation and region based similarity is proposed. This technique has combined effect of particle and region based approach.

Dempster-Shafer (D-S) evidence theory is proposed by Dempster in 1967, and extended by Shafer later. Dempster-Shafer (D-S) evidence theory is an effective method for decision fusion and has strong theoretical support. Compared with decision-making methods such as Bayes method, D-S theory can deal with the uncertainty of events caused by unknown and ambiguity. Additionally, assumption set can be narrowed down as the evidence accumulates [10].

D-S evidence theory is applied to integrate multiple features within the region merging process. The aspects of theory are

1) Definition of the frame of discernment,
2) The belief structure used to model the way a piece of source is assigned with a proposition,
3) Combination of beliefs from multisources,
4) A new merging cost based on d-s evidence theory.

In Particle Competition and Cooperation approach, first, each image pixel is converted into a graph node, which is connected to its k-nearest neighbors according to their visual features and location in the original image. Then, each labeled pixel generates a particle that will try to propagate its label to the unlabeled pixels. Furthermore, the particle dynamics are improved to decrease storage complexity and to allow the handling of larger images.

A "second phase" is also introduced to pick labels for nodes that are either undecided or that the particle approach have a low confidence regarding to the assigned label/segment. This scenario can be especially observed in border pixels or in pixels representing noise. Noise pixels do not share similar features with their neighborhood, thus they can become

Licensed Under Creative Commons Attribution CC BY

isolated nodes. Besides the nodes that represent noise pixels, whether the number of neighbors k is set to a low value, the graph might be composed of several components, and some of them can become unreachable by the particles. To avoid those problems, in the second phase, only the undecided pixels take collaboration from their neighbor pixels (in the original image) proportional to their feature similarity, in an iterative fashion until all labels become stable.

The following strategy will be followed to get the desired results.
Step 1: Implement the region based and particle competition-cooperation technique and design the new algorithm for image segmentation.
Step 2: Input the output of the region based approach to the particle competition and cooperation algorithm.
Step 3: Select simulation parameters like error rates.
Step 4: Compare the results of both the proposed and PCC for different types of images.

The parameter of evaluation is the error rate. The error rates are computed as the ratio of the number of incorrectly classified pixels to the total amount of unlabeled pixels.

4. Results

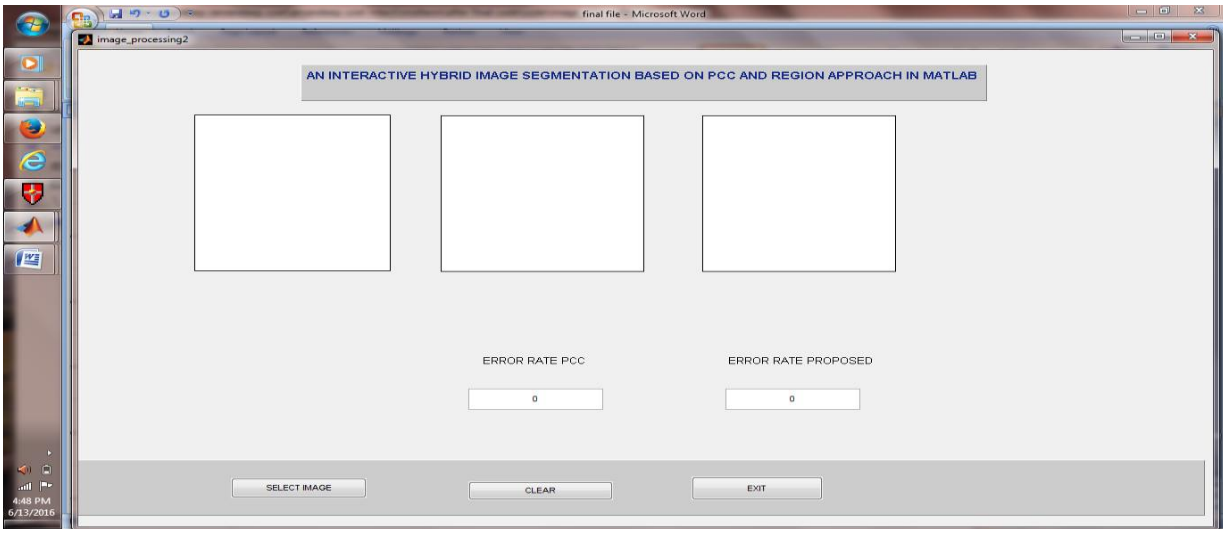

Figure 1: Graphical user interface of the proposed system

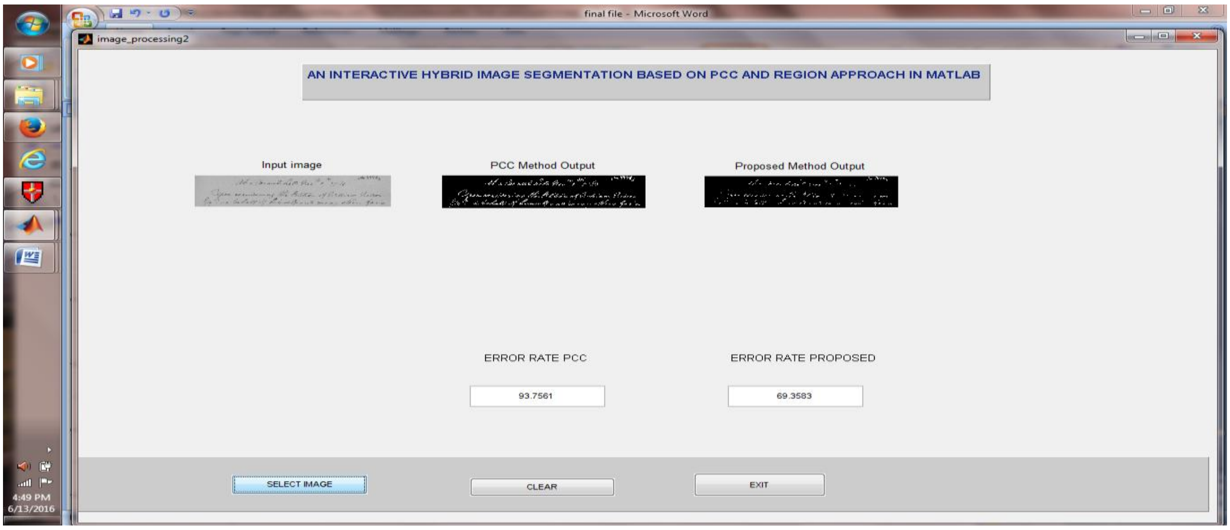

Figure 2: Result showing output of both methods on image H01

Licensed Under Creative Commons Attribution CC BY

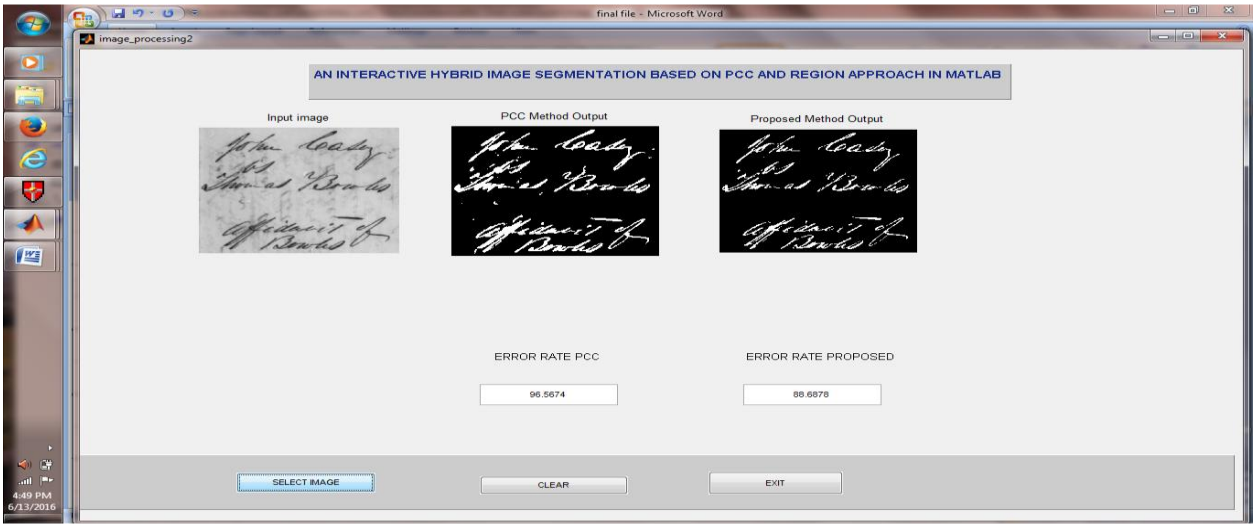

Figure 3: Result showing output of both methods on image H03

Figure 4: Result showing output of both methods on image P01

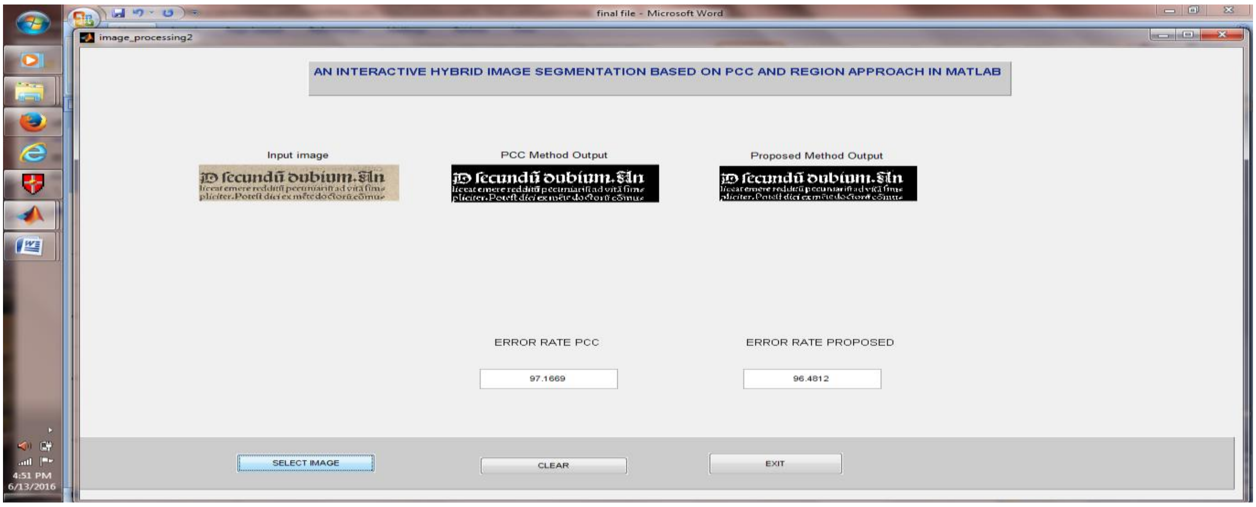

Figure 5: Result showing output of both methods on image P02

Licensed Under Creative Commons Attribution CC BY

5. Conclusion and Future Work

The results show that proposed method which is combined for of PCC and region based approach performs better than individual PCC method. Also the error rate is always minimum in case of proposed method. In the future work this proposed algorithm can be more enhanced so that error rate becomes more less so that better segmentation is achieved.

References

[1] L. Shapiro and G. Stockman, Computer Vision. Prentice Hall. 2001.
[2] R. C. Gonzalez and R. E. Woods, Digital Image Processing (3rd Edition). Upper Saddle River. NJ, USA: Prentice-Hall. Inc., 2008.
[3] X. Zhu, "Semi-supervised learning literature survey," Computer Sciences, University of Wisconsin-Madison, Tech. Rep. 1530, 2005.
[4] O. Chapelle, B. SchOikopf, and A. Zien, Eds., "Semi-Supervised Learning, ser. Adaptive Computation and Machine Learning." Cambridge, MA: The MIT Press, 2006.
[5] F. Breve, L. Zhao, M. Quiles, W. Pedrycz, and J. Liu, "Particle competition and cooperation in networks for semi-supervised learning," Knowledge and Data Engineering, IEEE Transactions on, vol. 24, no. 9, pp. 1686 -1698, 2012.
[6] F. Breve, M. G. Quiles and L. Zhao, "Interactive Image Segmentation using Particle Competition and Cooperation,"IEEE IJCNN, pp. 1-8, 2015.
[7] M. H. Jafari and S. Samavi, "Iterative Semi-Supervised Learning Approach for Color Image Segmentation," IEEE MVIP, pp. 76-79, 2015.
[8] A. Ducournau and A. Bretto, "Random walks in directed hypergraphs and application to semi-supervised image segmentation," Computer Vision and Image Understanding (120), pp. 91–102, 2014.
[9] F. Breve, "Combined Active and Semi-Supervised Learning using Particle Walking Temporal Dynamics," BRICS, pp. 15-20, 2013.
[10] Y. Yang, S. Han, T. Wang, W. Tao and X. Tai, "Multilayer graph cuts based unsupervised color-texture image segmentation using multivariate mixed student's t-distribution and regional credibility merging," Pattern Recognition, vol. 46, no. 4, pp. 1101-1124, 2013.
[11] I. Dopido, 1. Li, P. Marpu, A. Plaza, 1. Bioucas Dias and 1. Benediktsson, "Semisupervised Self-Learning for Hyperspectral Image Classification," IEEE Trans. Geosci. Remote Sensing, vol. 51, no. 7, pp. 4032-4044, 2013.
[12] J. Munoz-Mari, D. Tuia and G. Camps-Valls, "Semi supervised Classification of Remote Sensing Images With Active Queries," IEEE Trans. Geosci. Remote Sensing, vol. 50, no. 10, pp. 3751-3763, 2012.
[13] F. Breve and L. Zhao, "Particle Competition and Cooperation to Prevent Error Propagation from Mislabeled Data in Semi-Supervised Learning," IEEE BSNN, pp. 79-84, 2012.
[14] A. Frank and A. Asuncion, "UCI machine learning repository," 2010. [Online]
[15] Shuai Li, Lei Tao, Xiaojun Jing, Songlin Sun, Yueming Lu, Chenglin Zhao, Na Chen, "A Novel Region-based Image Segmentation Method Using SVM and D-S Evidence Theory", pp. 418-422, IEEE ISCIT, 2013.

Licensed Under Creative Commons Attribution CC BY