IJREAT International Journal of Research in Engineering & Advanced Technology, Volume 1, Issue 1, March, 2013
ISSN: 2320 - 8791
www.ijreat.org

Object Segmentation Using Probablistic Cue Points Technique

Nirmala K[1], Banupriya S[2] and Geetha R[3]

[1, 2, 3] Computer Science and Engineering
V.R.S College Of Engineering And Technology,Arasur,
Villupuram-607 107.

ABSTRACT

Segmentation means breaking a scene into non overlapping compact regions where each subdivided region constitutes pixels that are bound together on the basis of some relative similarity or dissimilarity measure. Identifying the specific object and recognizing the nature of the object is the wholesome idea of this project. The data embed in the images were grouped and it's segmented based on the relativity among the data. The difference among the contextual influences near to far from region boundaries makes neutral activities near region boundaries comparatively higher than elsewhere, making boundaries more predominant for perceptual segregation. Our proposed solution utilizes the probabilistic boundary edge map technique in which, the intensity of a pixel is set to be the probability to be either depth or contact boundary in the scene. The probability related to depth boundary can be determined by checking for a discontinuity of the pixel values in the optical flow map at the corresponding pixel location. We are utilizing static cues technique such as color and texture to, first, find all possible boundary locations in the image which are the edge pixels with positive color or texture gradient. After analysis, the probability of these edge pixels to be on depth and contact boundary is determined to identify the edge of an image objects in a picture. The maximum of two probability values is assigned as the probability of an edge pixel to be on object boundary. Finally project shows proposed method as an automatic segmentation framework and gives the text as output for the corresponding image.

1.INTRODUCTION

The human (primate) visual system observes and makes sense of a dynamic scene (video)or a static scene(or image) by making a series of fixations at various salient locations in the scene. The eye movement between consecutive fixations is called a saccade. Even during a fixation,the human eye is continuously moving. Such movement is called fixational movement. The main distinction between the fixational eye movements during a fixation and saccades between fixations is that the former is an involuntary movement whereas the latter is a voluntary movement. But the important question is: Why does the human visual system make these eye movements?

One obvious role of fixation he voluntary eye movements is capturing high resolution visual information from the salient locations in the scene as the structure of the human retina has a high concentration of cones (with fine resolution) in the central fovea. However, psychophysics suggests a more critical role of fixations in visual perception. For instance, during a change blindness experiment, the subjects were found to be unable to notice a change when their eyes were fixated at a location away from where the change had occurred in the scene unless the change altered the gist or the meaning of the scene. In contrast, the change is detected quickly when the subjects fixated on the changing stimulus or close to it. This clearly suggests a more fundamental role of fixation in how we perceive a scene (or image).
The role of fixational eye movements the involuntary eye movements during a fixation is even more unclear. In fact, for a long time, these eye movements were believed to be just a neural tick and not useful for visual perception. However,neuroscientists have recently revived the debate about the nature of these movements and their effects on visual perception.While we do not claim to know the exact purpose of these eye movements, we

certainly draw our inspiration from the need of the human visual system to fixate at different locations in order to perceive that part of the scene.We think that fixation should be an essential component of any developed visual system. We hypothesize that,during a fixation,a visual system at least segments the region it is currently fixating at in the scene (or image).We also argue that incorporating fixation into segmentation makes it well defined.

2.FIXATION-BASED SEGMENTATION: A WELL-POSED PROBLEM

In computer vision literature, segmentation essentially means breaking a scene into nonoverlapping, compact regions where each region constitutes pixels that are bound together on the basis of some similarity or dissimilarity measure. Over the years, many different algorithms have been proposed that segment an image into regions, but the definition of what is a correct or "desired" segmentation of an image (or scene) has largely been elusive to the computer vision community. In fact, in our view, the current problem definition is not well posed.To illustrate this point further, let us take an example of a scene (or image) shown in Fig. 1. In this scene, consider two of the prominent objects: the tiny horse and the pair of trees. Figs. 1b and 1c are the segmentation of the image using the normalized cut algorithm for different input parameters (these outputs would also be typical of many other segmentation algorithms). Now, if we ask the question:
Which one of the two is the correct segmentation of the image? The answer to this question depends entirely on another question: What is the object of interest in the scene? In fact, there cannot be a single correct segmentation of an image unless it has only one object in prominence, in which case the correct segmentation of the image is essentially the correct segmentation of that object.With respect to a particular object of interest the correct desired segmentation of the scene is the one wherein the object of interest is represented by a single or just a couple of regions. So, if the tiny horse is of interest, the segmentation shown in Fig. 1c is correct, whereas the segmentation shown in Fig. 1b is correct if the trees are of interest. Note, in Fig. 1b,the horse does not even appear in the segmentation. So, the goal of segmenting a scene is intricately linked with the object of interest in the scene and can be well defined only if the object of interest is identified and known to the segmentation algorithm beforehand.

Fig.1.Segmentation of a natural scene in (a) using the Normalized Cut algorithm for two different values of its input parameter (the expected number of regions) 10 and 60 are shown in (b) and (c), respectively.

But having to know about the object of interest even before segmenting the scene seems to make the problem one of many chicken-egg problems in computer vision, as we usually need to segment the scene first to recognize the objects in it. So, how can we identify an object even before segmenting it? What if the identification of the object of interest is just a weak identification such as a point on that object? Obtaining such points without doing any segmentation is not a difficult problem. It can be done using the visual attention systems, which can predict the locations in the scene that attracts attention.

The human visual system has two types of attention: overt attention (eyemovements) and covert attention(without eye movement). In this work, we mean overt attention whenever we use the term attention. The attention causes the eye to move and fixate at a new location in the scene. Each fixation will lie on an object, identifying that object (which can be a region in the background too) for the segmentation step. Now, segmenting that fixated region is defined as finding the "optimal" enclosing contour a connected set of boundary edge fragments around the fixation. This new formulation of segmenting fixated regions is a well-defined problem.

Note that we are addressing an easier problem than the general problem of segmentation where one attempts to find all segments at once.In the general segmentation formulation, the exact number of regions is not known and thus several ad hoc techniques have been proposed to estimate this number automatically. In fact, for a scene with prominent objects appearing at significantly different scales, having a single global parameter for segmenting the scene is not even meaningful, as explained.

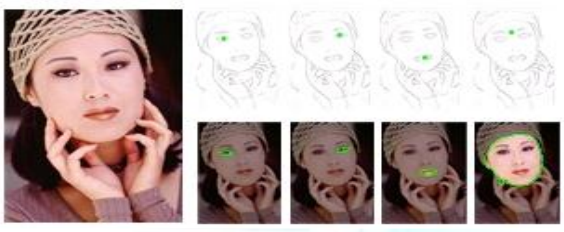

Fig. 2. The fixations, indicated by the green circular dots on the different parts of the face, are shown overlaid on the inverse probabilistic edge map of the leftmost image. The segmentation corresponding to every fixation as given by the proposed algorithm is shown right below the edge map with the fixation.

3.OVERVIEW

We propose a segmentation framework that takes as its input a fixation (a point location) in the scene and outputs the region containing that fixation. The fixated region is segmented in terms of the area enclosed by the "optimal" closed boundary around the fixation using the probabilistic boundary edgemap of the scene (or image). The probabilistic boundary edge map, which is generated by using all available visual cues, contains the probability of an edge pixel being at an object (or depth) boundary. The separation of the cue handling from the actual segmentation step is an important contribution of our work because it makes segmentation of a region independent of types of visual cues that are used to generate the probabilistic boundary edge map.The proposed segmentation framework is a two step process: First, the probabilistic boundary edge map of the image is generated using all available low-level cues.second, the probabilistic edge map is transformed into the polar space with the fixation as the pole and the path through this polar probabilistic edge map that "optimally" splits the map into two parts is found. This path maps back to a closed contour around the fixation point. The pixels on the left side of the path in the polar space correspond to the inside of the region enclosed by the contour in the Cartesian space, and those on the right side correspond to the outside of that region. Finding the optimal path in the polar probabilistic edge map is a binary labeling problem, and graph cut is used to find the globally optimal solution to this binary problem.

4.OUR CONTRIBUTIONS

The main contributions of this paper are:Proposing an automatic method to segment an object (or region) given a fixation on that object (or region)in the scene/image. Segmenting the region containing a given fixation point is a well-defined binary labeling problem in the polar space, generated by transforming the probabilistic edge map from the Cartesian to the polar space with fixation point as pole. In the transformed polar space, the lengths of the possible closed contours around the fixation points are normalized thus, the segmentation results are not affected by the scale of the fixated region. The proposed framework does not depend upon any user input to output the optimal segmentation of the fixated region. Since we carry out segmentation in two separate steps, it provides an easy way to incorporate feedback from the current segmentation output to influence the segmentation result for the next fixation by just changing the probabilities of the edge pixels in the edge map. See how it is used in a multifixation framework to refine the segmentation output. Also, the noisy motion and stereo cues do not affect the quality of the boundary as the static monocular edges provide better localization of the region boundaries and the motion and stereo cues only help pick the optimal one for a given fixation.

5. CONCLUSION

We proposed here a novel formulation of segmentation in conjunction with fixation. The framework combines static cues with motion and/or stereo to disambiguate between the internal and the boundary edges.The approach is motivated by biological vision, and it may have connections to neural models developed for the problem of border ownership in segmentation. Although the framework was developed for an active observer, it applies to image databases as well, where the notion of fixation amounts to selecting an image point which becomes the center of the polar transformation. Our contribution here was to formulate an old problem segmentation in a different way and show that existing computational mechanisms in the state of the art computer vision are sufficient to lead us to promising automatic solutions and finally we will find the expression of the face.

6.REFERENCES

[1] R. Achanta, S. Hemami, F. Estrada, and S. Susstrunk, "Frequency- Tuned Salient Region Detection," Proc. IEEE Conf. Computer Vision and Pattern Recognition, 2009.

[2] S. Alpert, M. Galun, R. Basri, and A. Brandt, "Image Segmentation by Probabilistic Bottom-Up Aggregation and Cue Integration," Proc. IEEE Conf. Computer Vision and Pattern Recognition,June 2007.

[3] P. Arbelaez and L. Cohen, "Constrained Image Segmentation from Hierarchical Boundaries," Proc. IEEE Conf. Computer Vision and Pattern Recognition, pp. 454-467,2008.

[4] S. Bagon, O. Boiman, and M. Irani, "What Is a Good Image Segment? A Unified Approach to Segment Extraction," Proc. 10thEuropean Conf. Computer Vision, pp. 30-44, 2008.

[5] A. Blake, C. Rother, M. Brown, P. Perez, and P. Torr, "Interactive Image Segmentation Using an Adaptive GMMRF Model," Proc. European Conf. Computer Vision, pp. 428-441, 2004.

[6] Y.Y. Boykov and M.P. Jolly, "Interactive Graph Cuts for Optimal Boundary and Region Segmentation of Objects in n-d Images," Proc. Eighth IEEE Int'l Conf. Computer Vision, pp. 105-112, 2001.

[7] Y.Y. Boykov and V. Kolmogorov, "An Experimental Comparison of Min-Cut/Max-Flow Algorithms for Energy Minimization in Vision," IEEE Trans. Pattern Analysis and Machine Intelligence,vol. 26, no. 9, pp. 1124-1137, Sept. 2004.