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OBJECT SEGMENTATION USING PROBABILISTIC CUE POINTS TECHNIQUE

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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

INTRODUCTION

The human eyes visualizes the environment by making fixed points in the scene which is of interest.the movement of eyes between these fixed points is called saccade.Even when the eye is focused on these fixed points,there is movement in the eyes.this is called fixational movements.the advantage of fixation is to capture high resolution images.an experiment called change blindness was conducted in which the person is made to focus on a particular point of scene.when a change occurred in other parts of the same scene the person is unable to recognize it.this helps us understand more about fixations.fixation is considered to be a involuntary movement whereas saccade is a voluntary movement [1].from this we understand that during fixation the human visual system segments the regin in the scene before fixation.

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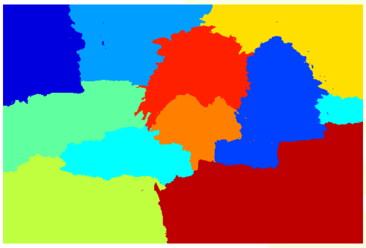
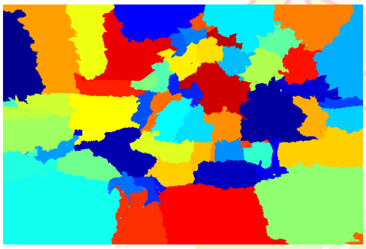
FIXED BASED SEGMENTATION

Segmentation means breaking a scene into nonoverlapping compact regions.let us take a axample of a scene

(a)



(b)



(c)

In this scene, consider two of the prominent objects: the tiny horse and the pair of trees.(b) and (c) are the segmentation of the image using cut algorithm [2] for input paramters 10 and 60.which can be considered as the corect segmentation of the image (b) or (c).the answer to this question lies on another question i.e what is the object of interest in the scene? So, if the tiny horse is of interest, the segmentationshown in Fig. 1c is correct, whereas the segmentation shown in Fig. 1b is correct if the trees are of interest. we usually need to segment the scene first to recognize the objects in it. So, how can we identify an object even before segmenting.

So to locate the object of interst may be a little complicated.but 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, [3], [4], [5]. which can predict the locations in the scene that attracts attention.

OVERVIEW

We propose a segmentation framework that takes 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 edge map of the scene (or image).

The proposed segmentation framework is a two step process: First, the probabilistic boundary edge map of the image is generated using all available low-

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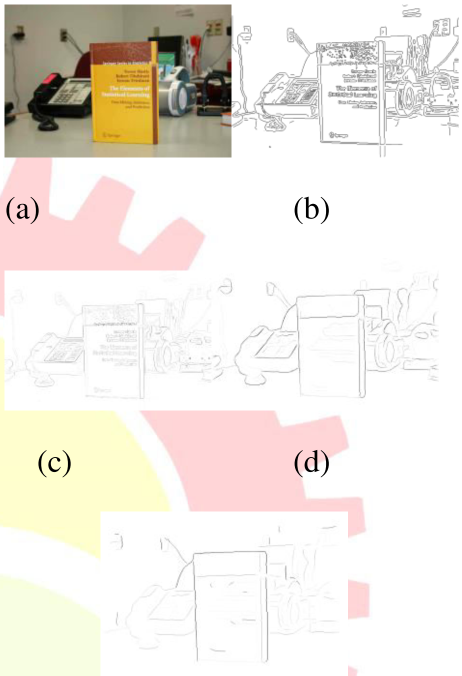
level cues. second, the probabilistic edge map is transformed into the polar space with the fixation as the pole. and the path through this polar probabilistic edge map that "optimally" splits the map into two parts is found.

PROPOSED PROBABILISTIC BOUNDARY EDGE MAP BY COMBINING CUES

generating the probabilistic boundary edge map using all available visual cues. There are two types of visual cues on the basis of how they are calculated: 1) static cues that come from just a single image; 2) stereo and motion cues that need more than one image to be computed. The static cues such as color, intensity, or texture can precisely locate the edges in the scene, but cannot distinguish between an internal texture edge from an edge at a depth discontinuity. On the other hand, stereo and motion can help distinguish between boundary and internal edge as there is a sharp gradient in disparity and flow across the former and no significant change across the latter.

Using Static Cues Only

For single images, we are going to use the output of the Berkeley edge detector as the probabilistic boundary edge map to segment the fixation regions.



(a) (b)

(c) (d)

(e)

Fig. 3. Inverse probabilistic edge maps of the color image shown in (a). Darker pixels mean higher probability. (b) The Canny edge map. (c) The gradient edge map. (d) The output of the Berkeley pb detector. (e) The final probabilistic boundary edge detector on combining static static cues with the motion cue.

Using stereo and static cues

Let us combine stereo with static cues. We compute a dense disparity map for a pair of rectified stereo pair using the algorithm proposed by Ogale and Aloimonos [6]. Let us say, the range of disparity values lies between 0 and

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maximum value D. Our objective here is to use these disparity values to decide if an edge pixel is at a depth discontinuity.

Depth discontinuity causes a sudden change in the disparity values and the amount of change depends on the actual physical depth variation at the edge and the camera configuration.Our approach to using relative disparity across the edge pixels to change their boundary probability is in agreement with the finding of the neurophysiological study [7].

Using Motion and Static Cues

Motion is different from stereo for two main reasons: First, unlike stereo, where a nonboundary edge does not have disparity change across it, an internal edge can also have a valid change in the flow across it. For instance, if a flat wheel is spinning along its axis, the flow vectors change direction across the spokes of the wheel, which are actually internal edges. Second, the optical flow vector representing motion information is a 2D vector, whereas the disparity is a scalar quantity making it easier to calculate their gradient than for the flow vector.

we calculate the absolute change in the x-component and y-component of the optical flow map across an edge pixel separately using the oriented circular discs.In our experiments with videos, we have used the optical flow algorithm proposed by Brox et al. [8].

AN INSIDE VERSUS OUTSIDE SEGMENTATION

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.

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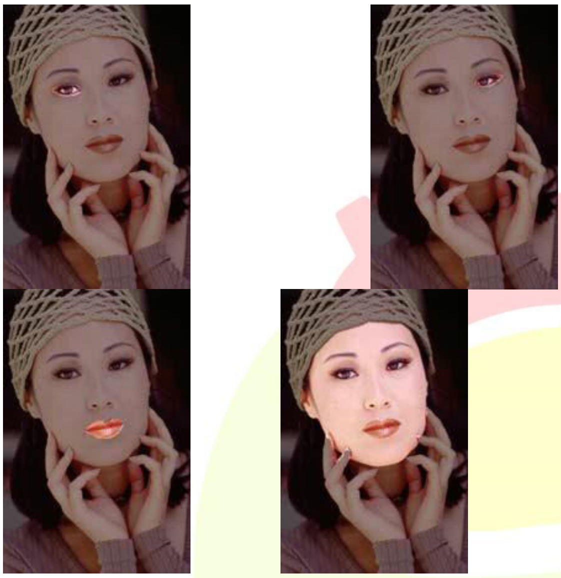

FIXATION STRATEGY

The proposed segmentation method clearly depends on the fixation point, and thus it is important to select the fixations automatically. Fixation selection is a mechanism that depends on the underlying task as well as other senses.

In the absence of such information, one has to concentrate on generic visual solutions. There is a significant amount of research done on the topic of visual attention [10], [7], [11], [12]. primarily to find the salient locations in the scene where the human eye may fixate. For our segmentation framework, as the next section shows, the fixation just needs to be inside the objects in the scene. As long as this is true, the correct segmentation will be obtained.Fixation points can be found using low-level features in the scene, [13], [14]. Although we do not yet have a definite way to automatically select fixations, we can easily generate potential fixations that lie inside most of the objects in a scene.

CONCLUSION

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

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