Active Segmentation with Fixation

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Abstract
The human visual system observes and understands a scene/image by making a series of fixations. Every “fixation point” lies inside a particular region of arbitrary shape and size in the scene which can either be an object or just a part of it. We define as a basic segmentation problem the task of segmenting that region containing the “fixation point”. Segmenting this region is equivalent to finding the enclosing contour – a connected set of boundary edge fragments in the edge map of the scene – around the fixation.

We present here a novel algorithm that finds this bounding contour and achieves the segmentation of one object, given the fixation. The proposed segmentation framework combines monocular cues (color/intensity/texture) with stereo and/or motion, in a cue independent manner. We evaluate the performance of the proposed algorithm on challenging videos and stereo pairs. Although the proposed algorithm is more suitable for an active observer capable of fixating at different locations in the scene, it applies to a single image as well. In fact, we show that even with monocular cues alone, the introduced algorithm performs as well or better than a number of image segmentation algorithms, when applied to challenging inputs.

1. Introduction
The human (primate) visual system observes and makes sense of a dynamic scene (video) or static scene (image) by making a series of fixations at various salient locations in the scene. Researchers have studied in great length about where human eye fixates [30, 12], but little is known about the operations carried out in the human visual system during a fixation. We hypothesize that during a fixation the human visual system at least segments the region containing that “fixation location” in the scene (or image). So, rather than segmenting the entire scene/image at once, it segments the scene in terms of individual regions for each of the fixations in the scene. For instance, in Fig. 1, the proposed algorithm segments two regions corresponding to the two different fixations on the two horses in the left image.

Since the early attempts on Active Vision [1, 5, 6, 19], there has been a lot of work on problems surrounding fixation, both from a computational and psychological perspective [23, 14]. It is also well known that the structure of the human retina is such that only the small neighborhood around the fixation is captured in high resolution by the fovea, while the rest of the scene is captured in lower resolution by the sensors on the periphery of retina. Despite knowing the significance of fixation in the human visual processing, however, the operation of fixation never really made it into the foundations of computational vision. Specifically, the fixation point has not been a parameter in the multitude of low and middle level computer vision algorithms. This is the avenue we want to pursue in this paper. We reformulate a fundamental problem in computer vision – segmentation – in conjunction with fixation.

A fixation always lies inside a region in the image and the region (or depth) boundary encloses all the points from inside the region including fixation. Segmenting this region then is equivalent to finding the enclosing contour - a connected set of boundary edge fragments in the edge map of the image - around the fixation. As the edge map contains both boundary (depth) and internal (texture/intensity) edges, it is important to be able to differentiate between the two types of edge fragments such that the boundary edge fragments are traced to from the enclosing contour. The edge pixels along the boundary edge fragments are assigned the higher intensity values than those along the internal edges. We call such edge map a probabilistic boundary...
edge map, the term borrowed from [20]. Here, the intensity of an edge pixel in the edge map is proportional to the probability that the edge pixel lies on a depth boundary. The enclosing contour for any fixation point in this probabilistic boundary edge map will thus be the “brightest” closed contour around it.

2. An overview: polar space is the key!

Let us consider finding the optimal contour for the red fixation on the disc shown in Fig.2a. The gradient edge map of the disc, shown in Fig.2b, has two concentric circles. The big circle is the actual boundary of the disc whereas the small circle is just the internal edge on the disc. The edge map correctly assigns the boundary contour intensity 0.78 and the internal contour 0.39. The intensity values range from 0 to 1. The lengths of the two circles are 400 and 100 pixels. Now, the cost of tracing the boundary and the internal contour in the Cartesian space will be 88 = (400 × (1 − 0.78)) and 61 = (100 × (1 − 0.39)).

Clearly, the internal contour costs less and hence will be considered optimal even though the boundary contour is the brightest and should actually be the optimal contour. In fact, this problem of inherently preferring short contours over long contours has already been identified in the graph cut based approaches where the minimum cut usually prefers to take “short cut” in the image [27].

To fix this “short cut” problem, we have to transfer these contours to a space where their lengths no longer depend upon the area they enclose in the Cartesian space. The cost of tracing these contours in this space will now be independent of their scales in the Cartesian space. The polar space has this property and we use it to solve the scale problem. The contours are transformed from the Cartesian co-ordinate system to the polar co-ordinate system with the red fixation in Fig.2b as the pole. In the polar space now, both contours become open curves (0° − 360°). See Fig.2c. Thus, the costs of tracing the inner contour and the outer contour become 80.3 = 365 × (1 − 0.78) and 220.21 = 361 × (1 − 0.39) respectively. As expected, the outer contour (the actual boundary contour) costs the least in the polar space and hence becomes the optimal enclosing contour around the fixation.

It is important to make sure that the optimal path in the polar space is stable with respect to the location of the fixation, meaning as the fixation moves to a new location the optimal path in the polar space for the new fixation should correspond to the same closed contour in the Cartesian space. For the new fixation (the green “X”) in Fig.2b, both contours have changed shape (See Fig.2d), but the brightest contour still remains optimal. A detailed stability analysis is done in section 8.1.

The method proposed in this paper to segment a region for a fixation is a two step process: first, the probabilistic boundary edge map of the image is generated using all available low level cues (section 3); second, this probabilistic edge map is transformed into the polar space with the fixation as the pole (section 4), and the path through this polar probabilistic edge map (the blue line in Fig.3g) that optimally splits the map into two parts (Fig.3f) is found in section 5. 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. So, finding the optimal path in the polar probabilistic edge map is equivalent to segmenting it into inside and outside region which is a binary labeling problem. Graph cut is used to find globally optimal solution to this binary segmentation problem (see section 5). Note that we are addressing an easier problem than the general problem of segmentation where one attempts to find all segments at once.

The main contributions of this paper are:
1. Proposing an automatic method to segment a region for every fixation point in the scene/image
2. Integrating cues without changing the segmentation framework

3. Probabilistic boundary edge map by combining cues

In this section, we explain how to generate the probabilistic boundary edge map wherein the boundary edges (or the depth boundaries) are bright and the internal (texture/intensity) edges are dim. The output of the Berkeley edge detector [20] is our initial probabilistic boundary edge map. In [20], Martin et al. learned the color and texture properties of the boundary pixels versus non-boundary pixels from the labeled data (300 images segmented by human subjects) and use that information to differentiate the boundary edges from the internal edges. See Fig.3b, the Berkeley edge map of the image in Fig.3a. Clearly, the spurious texture edges are removed and the boundary edges are strong (bright), but it still has some strong internal edges (BC, CD, CF).

Now, to suppress these strong internal edge segments and
reinforce the boundary edges (AG, GH, HE, EA), we use motion or/and stereo cues. We know that the change in disparity or flow across the boundary edges is far greater than that across the internal edges. So, we break the edge map into straight line segments and select rectangular regions of width $w$ at a distance $r$ on its both sides. We choose $r$ and $w$ to be 5 and 10 pixels in our experiments. For example, in Fig.3c, the line segments FC and FA are shown with the rectangular regions on their sides. We calculate the average disparity and/or average flow inside these rectangles. The difference in the average disparity and the magnitude of the average flow on both sides are the measure of the likelihood of the segment to be the depth boundary. Let us say, $\Delta d$ and $\Delta f$ represent the change in disparity and flow respectively. The reason to select the rectangular regions at a distance $r$ away from the edge segment is to avoid corrupted flow or disparity values along the depth boundaries.

The brightness of an edge pixel on the segment is changed as $I'(x,y) = \alpha_bI(x,y)+(1-\alpha_b)(\Delta f/\max(\Delta f))$ or $I'(x,y) = \alpha_bI(x,y) + (1-\alpha_b)(\Delta d/\max(\Delta d))$ for motion and stereo cues respectively. $\alpha_b$ is the weight associated with the relative importance of the monocular cue based boundary estimate. For our experiments, we chose $\alpha_b$ to be 0.2. The final boundary edge map is shown in Fig.3d wherein the internal edge are dim and the boundary edges are bright. With the improved boundary edge map, as the algorithm traces the brightest closed contour (AGHEA) around the fixation point, it will also be the real depth boundary of the region containing the fixation (Fig.3e).

In the final boundary edge map, the image borders are also added as edges to ensure enclosedness for the fixations lying on the regions partially present in the image. See the car in the column 5 of Fig.6 (A part of its closed boundary is the left border of the image.) The intensity of the edges corresponding to image borders is kept low such that they are not preferred over real edges.

4. Cartesian to polar edge map

Let’s say, $I^\text{cart}_{E}(\cdot)$ is an edge map in Cartesian coordinate, $I^\text{pol}_{E}(\cdot)$is its corresponding polar plot and $F(x_o,y_o)$ is chosen as a pole. Now, a pixel $I^\text{pol}_{E}(r,\theta)$ in the polar coordinate system corresponds to a sub-pixel location $\{(x,y): x=r\cos\theta+x_o, y=r\sin\theta+y_o\}$ in the Cartesian coordinate system. $I^\text{cart}_{E}(x,y)$ is typically calculated by bi-linear interpolation which only considers four immediate neighbors.

We propose to generate a continuous 2D function $W(.)$ by placing 2D Gaussian kernel functions on every edge pixel. The major axis of these Gaussian kernel functions is aligned with the orientation of the edge pixel. The variance along the major axis is inversely proportional to the distance between the edge pixel and the pole $O$. Let $E$ be the set of all edge pixels. The intensity at any sub-pixel location $(x,y)$ in Cartesian coordinates is

$$W(x,y) = \sum_{e\in E} \exp\left(-\frac{x'^2}{\sigma^2_{xe}} - \frac{y'^2}{\sigma^2_{ye}}\right) \times I^\text{cart}_{E}(xe, ye)$$
\[
\begin{bmatrix}
  x'_{r e} \\
  y'_{r e}
\end{bmatrix} =
\begin{bmatrix}
  \cos \theta_e & -\sin \theta_e \\
  \sin \theta_e & \cos \theta_e
\end{bmatrix}
\begin{bmatrix}
  x_e - x \\
  y_e - y
\end{bmatrix},
\]
where \( \sigma^2_{r e} = \frac{K_1}{(x_e - x)^2 + (y_e - y)^2} \), \( \sigma^2_{\theta e} = K_2 \). \( \theta_e \) is the orientation at the edge pixel \( e \), \( K_1 = 900 \) and \( K_2 = 4 \) are constants. The reason for setting the square of variance along the major axis, \( \sigma^2_{r e} \), to be inversely proportional to the distance of the edge pixel from the pole is to keep the gray values of the edge pixels in the polar edge map the same as the corresponding edge pixel in the Cartesian edge map. The intuition behind using variable width kernel functions for different edge pixels is as follows: Imagine an edge pixel being a finite sized elliptical bean aligned with its orientation, and you look at it from the location chosen as pole. The edge pixels closer to the pole (or center) will appear bigger and those farther away from the pole will appear smaller.

The polar edge map \( I^\text{pol}(r, \theta) \) is calculated by sampling \( W(x, y) \). The intensity values of \( I^\text{pol} \) are scaled to lie between 0 and 1. An example of this polar edge map is shown in Fig.3h. Our convention is that the angle \( \theta \in [0^\circ, 360^\circ) \) varies along the vertical axis of the graph and increases from the top to the bottom whereas the radius \( 0 \leq r \leq r_{\text{max}} \) is represented along the horizontal axis increasing from left to the right. \( r_{\text{max}} \) is the maximum Euclidean distance between any two locations in the image.

### 5. Finding the optimal cut through the polar edge map: an inside vs outside segmentation

Let us consider every pixel \( p \in P \) of \( I^\text{pol} \) as a node in a graph. Every node (or pixel) is connected to their 4 immediate neighbors (Fig. 4). A row of the graph represents the ray emanating from the fixation point at an angle \( (\theta) \) equal to their row index. The first and the last rows of this graph are the rays \( \theta = 0^\circ \) and \( \theta = 360^\circ \) respectively which are essentially the same ray in the polar representation. Thus, the pairs of nodes \( \{(0^\circ, r), (360^\circ, r)\} \) \( \forall r \in [0, r_{\text{max}}] \) should be connected by edges in the graph. The set of all the edges between neighboring nodes in the graph is denoted by \( \Omega \). Let us assume \( l = \{0, 1\} \) are the two possible labels for each pixel where \( l_p = 0 \) indicates ‘inside’ and \( l_p = 1 \) denotes ‘outside’. The goal is to find a labeling \( f(P) \mapsto l \) that corresponds to the minimum energy where the energy function is defined as:

\[
Q(f) = \sum_{p \in P} U_p(l_p) + \lambda \sum_{(p, q) \in \Omega} V_{p, q} \delta(l_p, l_q)
\]

\[
V_{p, q} = \begin{cases} 
\exp(-\eta I^\text{pol}_{E, pq}) & \text{if } I^\text{pol}_{E, pq} \neq 0 \\
k & \text{otherwise}
\end{cases}
\]

where \( \lambda = 50 \), \( \eta = 5 \), \( \lambda = 20 \), \( I^\text{pol}_{E, pq} = (I^\text{pol}_e(r_p, \theta_p) + I^\text{pol}_e(r_q, \theta_q))/2 \), \( U_p(l_p) \) is the cost of assigning a label \( l_p \) to the pixel \( p \) and \( V_{p, q} \) is the cost of assigning different labels to the neighboring pixels \( p \) and \( q \).

At the start, there is no information about how the inside and outside of the region containing the fixation looks like. So, the data term \( U(.) \) for all the nodes in the graph except those in the first column and the last column is zero: \( U_p(l_p) = 0 \), \( \forall p \in (r, \theta), 0 < r < r_{\text{max}}, 0^\circ \leq \theta < 360^\circ \). However, the nodes in the first column which correspond to the fixation point in the Cartesian space must be inside and are initialized to the label 0: \( U_p(l_p = 0) = D \) and \( U_p(l_p = 0) = 0 \) for \( p \in (0, \theta), 0^\circ \leq \theta < 360^\circ \). The nodes in the last column on the other hand must lie outside the region and are initialized to the label 1: \( U_p(l_p = 0) = D \) and \( U_p(l_p = 1) = 0 \) for \( p \in (r_{\text{max}}, \theta), 0^\circ \leq \theta < 360^\circ \). See Fig.4. In our experiments, we choose \( D \) to be 1000; the high value is in order to make sure the initial labels to the first and the last columns do not change as a result of minimization. We use the graph cut algorithm [10] to minimize the energy function, \( Q(f) \). The resulting binary segmentation is transferred back to the Cartesian space to get the desired segmentation. Fig.5c shows the segmentation for the fix (the green “X”) in the image Fig.5a.

The binary segmentation step explained above splits the polar edge map into two parts: left side (inside) and right side (outside). See Fig. 3f. The color information on the left (inside) and the right (outside) can now be used to change the data term. \( U_p(.) \) which otherwise was zero for most of the pixels. The color information at a pixel in the polar image \( (I^\text{rgb}_e(r, \theta)) \) is obtained by interpolating the RGB value at the corresponding sub-pixel location in the Cartesian space. See Fig.3f for an example of such a \( I^\text{rgb}_e(r, \theta) \). Let us say, \( F_{\text{in}}(r, g, b) \) and \( F_{\text{out}}(r, g, b) \) represent the color distributions of the inside and outside respectively. These distributions are normalized three dimensional histograms with 10 bins along each color channel. The data term for all the nodes except those in the first and last columns becomes:

\[
U_p(l_p) = \begin{cases} 
-\ln(F_{\text{in}}(I^\text{pol}_e(r_p, \theta_p))) & \text{if } l_p = 0 \\
-\ln(F_{\text{out}}(I^\text{pol}_e(r_p, \theta_p))) & \text{if } l_p = 1
\end{cases}
\]

where \( Z_p = \ln(F_{\text{in}}(I^p(r_p, \theta_p))) + \ln(F_{\text{out}}(I^p(r_p, \theta_p))) \). We then use the graph cut algorithm again to minimize the modified energy function, \( Q(f) \) with new data term. The segmentation result improves after introducing the color information in the energy formulation. See Fig.5c and d. The boundary between the left (label 0) and the right (label 1)
are needed. Although these approaches give impressive re-ground/background segmentation, at least two seed points requires a seed point for every region in the image. For foreground and background models. [24] requires users to specify the center of the star shape exactly in the image. [4] needs only one seed point to be specified on the region of interest and segment the foreground region using a compositional framework. But the algorithm is computationally intensive. It runs multiple iterations to arrive at the final segmentation.

There is a huge literature on segmenting regions in images and videos. All segmentation algorithms depend upon some form of user inputs, without which the definition of the optimal segmentation of an image is ambiguous. Also, these algorithms always segment the entire image at once. There are two broad categories: first, the segmentation algorithms [26, 15, 28] that need the user-specified global parameters such as the number of regions and thresholds to stop the clustering; second, the interactive segmentation algorithms [9, 31, 4, 24] that always segment the entire image into only two regions: foreground and background. [9] poses the problem of foreground/background segmentation as a binary labeling problem which is solved exactly using the maxflow algorithm [8]. It, however, requires users to label some pixels as foreground or background to build their color models. [7] improved upon [9] by using a Gaussian mixture Markov random field to better learn the foreground and background models. [24] requires users to specify a bounding box containing the foreground object. [3] requires a seed point for every region in the image. For foreground/background segmentation, at least two seed points are needed. Although these approaches give impressive results, they can not be used as an automatic segmentation algorithm as they critically depend upon the user inputs. [31] tries to automatically select the seed points by using spatial attention based methods and then use these seed points to introduce extra constraints into their normalized cut based formulation.

Unlike the interactive segmentation methods mentioned above, [29, 4] need only a single seed point from the user. [29] imposes a constraint on the shape of the object to be a star, meaning the algorithm prefers to segment the convex objects. Also, the user input for this algorithm is critical as it requires the user to specify the center of the star shape exactly in the image. [4] needs only one seed point to be specified on the region of interest and segment the foreground region using a compositional framework. But the algorithm is computationally intensive. It runs multiple iterations to arrive at the final segmentation.

7. Results

We evaluated the performance of the proposed algorithm on 20 videos with average length of seven frames and 50 stereo pairs with respect to their ground-truth segmentation. (The source code of our implementation is available at http://www.umiacs.umd.edu/~mishraka/activeSeg.html.) For each sequence and stereo pair, only the most prominent object of interest is identified and segmented manually to create the ground-truth foreground and background masks. The fixation is chosen randomly anywhere on this object of interest. The videos used for the experiment are of all types: stationary scenes captured with a moving camera, dynamic scenes captured with a moving camera, and dynamic scenes captured with a stationary camera.

The segmentation output of our algorithm is compared with the ground truth segmentation in terms of the F-measure defined as \(2PR/(P + R)\) where \(P\) stands for the precision which calculates the fraction of our segmentation overlapping with the ground truth, and \(R\) stands for recall which measure the fraction of the ground-truth segmentation overlapping with our segmentation.

Table 1 shows that after adding motion or stereo cues with color and texture cues the performance of the proposed
method improves significantly. With color and texture cues only, the strong internal edges prevent the method from tracing the actual depth boundary. (See Fig.6 Row 2). However, the motion or stereo cues clean the internal edges as described in section 3 and the proposed method finds the correct segmentation (Fig.6 Row 3).

To also evaluate the performance of the proposed algorithm in the presence of the monocular cues only, the images from the Alpert image database [2] has been used. The Berkeley edge detector [20] provides the probabilistic boundary maps of these images. The fixation on the image is chosen at the center of the bounding box around the foreground. Our definition of the segmentation for a fixation is the region enclosed by the depth boundary which is difficult to find with the monocular cues only. Table 2 shows that we perform better than [26, 28] and close to [2, 4]. The definition of segmentation in [4] is such that for a selected seed on any of the two horses in Fig.1a, both horses will be segmented while our segmentation finds only the horse seed on any of the two horses in Fig.1a, both horses will.

### 8. Fixation Strategy

The proposed 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 (like sound). In the absence of these cues, one has to concentrate on generic visual solutions. There is a significant amount of research done on the topic of visual attention [30, 16, 25, 11] 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 amount to features in the scene and the recent literature on features comes in handy[18, 22]. Although we do not yet have a definite way to automatically select fixations, we can easily generate the potential fixations that lie inside most of the objects in a scene. Fig.8 shows multiple segmentation using this technique.

#### 8.1. Stability Analysis

Here, we verify our claim that the optimal closed boundary for any fixation inside a region remains same. The possible variation in the segmentation will occur due to the presence of bright internal edges in the probabilistic boundary edge map. To evaluate the stability of segmentation with respect to the location of fixation inside the object, we devise the following procedure: Choose a fixation roughly at the center of the object and calculate the optimal closed boundary enclosing the segmented region. Calculate the average scale, $S_{avg}$, of the segmented region as $\sqrt{\text{Area}/\pi}$. Now, the new fixation is chosen by moving away from the original fixation in random direction by $n \cdot S_{avg}$ where $n = \{0.1, 0.2, 0.3, ..., 1\}$. If the new fixation lies outside the original segmentation, a new direction is chosen for the same radial shift until the new fixation lies inside the original segmentation. The overlap between the segmentation with respect to the new fixation, $R_n$, and the original segmentation, $R_o$, is given by $\frac{|R_o \cap R_n|}{|R_o|}$.

We calculated the overlap values for 100 textured regions and 100 smooth regions from the BSD and Alpert Segmentation Database. It is clear from the graph Fig.9a that the overlap values are better for the smooth regions than for the textured regions. Textured regions might have Strong internal edges making it possible for the original optimal path to

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>F-measure score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bagon et al. [4]</td>
<td>0.87 ± 0.010</td>
</tr>
<tr>
<td>Alpert et al. [2]</td>
<td>0.86 ± 0.012</td>
</tr>
<tr>
<td>Our Method</td>
<td>0.83 ± 0.019</td>
</tr>
<tr>
<td>NCut [26]</td>
<td>0.72 ± 0.012</td>
</tr>
<tr>
<td>MeanShift [28]</td>
<td>0.57 ± 0.023</td>
</tr>
</tbody>
</table>

Table 2. One single segment coverage results. The scores for other methods except [4] are taken from [2].
modify as the fixation moves to a new location. However, for the smooth regions, there is a stable optimal path around the fixation, it does not change dramatically as the fixation moves to a new location. We also calculate the overlap values for the 100 frames from video sequences; first with their boundary edge map given by [20] and then using the enhanced boundary edge map after combining motion cues. The results are shown in Fig.9b. We can see that the segmentation becomes stable as motion cues suppress the internal edges and reinforce the boundary edge pixels in the boundary edge map [20].

9. Conclusion

We proposed here a novel formulation of segmentation in conjunction with fixation. The framework combines monocular cues with motion and/or stereo to disambiguate the internal edges from 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[13]. 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. Our approach can be complemented in a variety of ways, for example by introducing a multitude of cues. An interesting avenue has to do with learning models of the world. For example, if we had a model of a "horse", we could segment the horses more correctly in Fig1. This interaction between low level bottom up processing and high level top down attentional processing, is a fruitful research question.

References