Segmentation of Medical Images Using Directional Force Active Contour Models

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ABSTRACT

A new technique for automatic extraction of object region and boundary from the background for cell nucleus segmentation of cervical cancer images is proposed in this work. Gradient magnitude and directional information are employed to extract the exact boundary of the object under consideration. Segmentation process begins with preprocessing as computation of optimum threshold based on the clusters automatically from K-means clustering algorithm. The cluster center of this threshold region, act as a seed for further processing. The problem of extracting the gradient information from concave boundaries is addressed by the use of gradient vector flow snake. The active contour has been found using convergence Index filter to find the exact boundary using directional information if the magnitude differentiation is less in the low intensity image like cell medical images. Then the object region is extracted from the object boundary and gray scale cluster. The advantage of this method is that it does not require any initial approximate contour or any seed point like parametric active contour model or any priori knowledge about the image characteristics. Further the segmentation speed of this algorithm also empowers real time execution possible for any general image applications.

Key Words: Gradient vector field, Convergence index filter, active contour model, region filling, Segmentation.

1. INTRODUCTION

Active contours can be used as elastic curves when it moves from outside to the object boundary and balloon force if it is from inside the object [2]. These elastic curves are deformed and its deformations are controlled by image features and shape constraints. The deformable contour is generally classified as parametric active contour model and geometric active contour model. This paper focuses on parametric active contour model [4].

Parametric active contour model synthesize parametric curve within the image domain and allow them to move towards the desired features usually edges. Typically the curves are drawn towards the edges by potential forces, which are defined to be the negative gradient of a potential function [1]. Additional forces such as pressure force together with the potential force comprise the external forces. One of the difficulties of parametric active contour algorithm is initial contour assumption. And it should be close to the region of interest to get accurate boundary or else it likely cover the wrong result. Several methods address this problem with their own technologies [9][10]. One of the methods called Gradient Vector Flow, to cover the increased potential area for accurate boundary detection by Lu and Prince [4].

In this paper we propose an additional external force field as directional information along with the magnitude. This process is formulated to obtain cell nuclear segmentation of cervical cancer cell images. Normally medical images are very low intensity in nature. Here the Convergence Index Filter (COIN)[5] which filters the result regardless of the contrast and works based on the directional information is used to find the directional parameter. This increased capture range [2,4]is achieved through diffusion process that does not blur the edge themselves. So multi resolution methods are not needed. Using these potential forces, the closed contour of the image has been found. Then region filling algorithm is used to segment the images. For this region filling process the clustering seed points are used, which is calculated using k-means clustering algorithm as a preprocessing.

The following sections are organized as follows. Section II deals with the review and concept of Active contour models, GVF and COIN filter which can be effectively treated in our algorithm. In section III we
2. BACK GROUND

2.1. Parametric Active Contour Models

The snake is a contour represented parametrically as \( c(s) = (x(s), y(s)) \) where \( x(s) \) and \( y(s) \) are the coordinates along the contour and \( s \in [0, 1] \). All snake properties and its behavior is specified through a function called energy functional by analogy with physical systems. A force is acting upon the curve and it is moving across the landscape trying to reach the energy equilibrium the energy functional used is a sum of several terms, each corresponding to some force acting on the contour.

Total energy of the snake

\[
E_{\text{Energy}} = E_{\text{internal}} + E_{\text{external}} - \frac{1}{2}
\]

Where

\[
E_{\text{external}} = -\sum_{i=1}^{n} \left| G_x(x_i, y_i) \right|^2 + \left| G_y(x_i, y_i) \right|^2
\]

\[
E_{\text{internal}} = \sum_{i=1}^{n} \left( \alpha \left| v_i - v_{i-1} \right|^2 + \beta \left| v_{i-1} - 2v_i + v_{i+1} \right|^2 \right)
\]

The snake was to minimize the energy functional in order to achieve equilibrium is defined as following equation

\[
E = \frac{1}{2} \int_0^1 \left( \frac{1}{2} \left| X'(s) \right|^2 + \beta \left| X''(s) \right|^2 \right) + E_{\text{ext}}(X(s)) ds
\]

where \( \alpha \) and \( \beta \) re weighting parameters that control the snake’s tension and rigidity, respectively, and \( X' \) denote the first and \( X'' \) second derivatives of with respect to \( s \). \( E_{\text{internal}} \) internal force discourages stretching and bending while the \( E_{\text{external}} \) external potential force pulls the snake toward the desired image edges. In order to reveal the poor convergence in the boundary concavity and the limited captured range of the gradient field can be extended with GVF field.

2.2. Gradient Vector Flow Snake

The GVF field is defined as a force field of vectors. The vector

\[
V(x, y) = [u(x, y), v(x, y)]
\]

for any image pixels is computed by minimizing the energy functional as

\[
\epsilon = \iint \mu \left( u^2_x + u^2_y + v^2_x + v^2_y \right) + |V f|^2 |V - \nabla f| dx dy
\]

This variation formulation follows a standard principle that of making the result smooth when there is no data. In particular, when \( \nabla f \) is small; the energy is dominated by sum of the squares of the partial derivatives of the vector field, yielding a slowly varying field. On the other hand, when \( \nabla f \) is large, the second term dominates the integrand, and is minimized by setting \( v = \nabla f \). This produces the desired effect of keeping \( v \) nearly equal to the gradient of the edge map when it is large, but forcing the field to be slowly-varying in homogeneous regions. The parameter \( \mu \) is a regularization parameter governing the tradeoff between the first term and the second term in the integrand. This parameter should be set according to the amount of noise present in the image (more noise, increase). Normally it has to be set \( 0 - 0.25 \).

2.3. Convergence Index Filter

The convergence index is a measure of how strongly the gradient vectors point toward the pixel of interest. It is evaluated in the neighborhood of the pixel of interest, denoted by \( R \) which is the region of support of the proposed filter. As shown in Fig. 1, it is a rounded region with a radius \( r \) whose center is at the pixel of interest \( P \). Let us denote an arbitrary pixel \( R \) in and its relative coordinates \( f(k, l) \) respectively. The angle \( \theta(k, l) \) is, as shown in Fig. 1, the orientation of the gradient vector \( g(k, l) \) with respect to the line \( PQ \). We adopt \( \cos \theta(k, l) \) as the convergence index of a gradient vector at \( (k, l) \).

The output of the convergence index filter is defined as the average of the convergence indices at all pixels in \( R \) as follows:

\[
C(i, j) = \frac{1}{M} \sum_{(k, l) \in R} \cos \theta(k, l)
\]

Where \( M \) is the number of pixels in \( R \). The output of the COIN filter falls between -1 and +1. At the maximum value of +1, all the gradient vectors in \( R \) point toward the pixel of interest. This occurs if equi-contours of the intensity \( I(i, j) \) in the neighborhood of the pixel of interest are concentric.

If the gradient vector field is uniform, the COIN filter shows a near zero output. The theoretical output of the coin filter for a rounded convex region is shown in above figure. This is defined here as a region whose intensity equi contours is concentric. Also, all gradient vectors point toward its center. The output level at
the boundary is $1/\pi$, regardless of the contrast between the rounded convex region and the background in the original image.

3. PROPOSED SYSTEM

Our new segmentation algorithm is based on active contour model is different from traditional snake algorithm for finding the closed contours for segmentation. The drawback of initial contour assumption and concavity finding in the traditional snake model has been overcome by the method of regional classification using clustering and GVF (Gradient vector flow). Normally the gradient magnitude is used as an external force in the traditional snake algorithm. Here we propose another force called directional force. Object and non-object pixels can be isolated based on the varying intensity. Medical images are normally very low in contrast. If they are very weak contrast it is difficult to use magnitude to classify the pixels. Here the convergence index filter (COIN) whose performance does not depend on the contrast is employed for detecting object region. The flow amplitude and direction of the GVF field are used to compute the kernel of the COIN filter. The kernel operates over the gradient energy field to classify the pixels. The sum of cosine of differences of angles (angles between the line connecting origin and the gradient vector of every point) will be early equal to 1 if it is a object region, it will be near to zero or if it will not be a object region. The filtered output is based on the directional information. So the blurriness of the image is not affecting the output. The boundary of the image has identified based on the filtered output and also classified as object pixel and non-object pixel. Then the flood fill algorithm is used to segment the image from the background.

The algorithm proposed in this paper follows the general flow of active contour algorithm. But it is based on the evaluation of region based classification. The contour is implicitly as the boundary of the region. The main advantage of this approach is the elimination of initial contour assignments, concavity finding and energy minimization iterations which is time consuming when iteratively on the processor array. Further more proposed system implements contour evaluation using very simple region classification, magnitude and directional information which results a accurate contour in fast implementation.

3.1. Regional Classification and Seed Detection

For multiplear scale edge detection for accurate segmentation, that means extracting objects from background, we need good detection of object boundaries. The traditional edge detection algorithm shows all the edges, which are inside and outside the object as well as noise in the image not exactly of object boundaries. But from the regional classification output from the K-means if we get an edge using canny edge detector it will show the reduced number of edges, which we wanted for our boundary detection.
An automatic clustering process is considered an unsupervised learning process, because it can automatically reveals, intrinsic categorical patterns. Different similarity measure can result in different cluster results. The algorithm starts with guess about the cluster centroid, and based on the simple iterative scheme and finds the local optimum.

\[ J = \sum_{k} \sum_{n} \left\| x_{ij} - c_{j} \right\|^2 \]  \hspace{1cm} (5)

The function defines the shortest distance difference between \( c_{j} \) (centroid) and the item \( x_{i} \). The process starts with cluster value as 2 and repeated until the cluster seed points have been calculated. This seed points are used in the region growing algorithm which is explained in section C.

### 3.2. Energy Minimization using GVF- COIN Filter

Object boundaries have larger magnitude compared with the interior or external pixels. The GVF field is defined as a force field of vectors. The vector \( Gr(x,y) \) and \( Gc(x,y) \) denoted the row and col gradients and the orientation of the G is given by the angle

\[ \phi(x,y) = \tan^{-1} \frac{Gc(x,y)}{Gr(x,y)}. \]  \hspace{1cm} (6)

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**Figure 3b:** Canny Output after Region Classification

**Figure 4:** Seed Value are 68,130 Hsil.jpg Image-histogram

**Figure 5:** Seed Values are 84,119 Lsil.jpg -histogram

**Figure 6:** Output of Normal Gradient-part of Cervical Cancer Cell

**Figure 7:** GVF Output of Part of Cervical Cancer Cell
Several properties can be observed from these figures. First, the capture ranges of the GVF force field and the distance potential force field are clearly much larger than that of the traditional potential force field. In fact, both distance potential forces and GVF forces will attract a snake that is initialized on the image border. Second, it is clear that GVF is the only force providing both a downward force within the boundary concavity. In contrast, both traditional snake forces and distance potential forces provide only sideways forces in these regions. Third, the distance potential forces appear to have boundary points that act as regional points of attraction. In contrast, the GVF forces attract points uniformly toward the boundary.

### Table 1
Directional Flow of GVF

<table>
<thead>
<tr>
<th>Vector</th>
<th>Direction</th>
</tr>
</thead>
<tbody>
<tr>
<td>U</td>
<td>V</td>
</tr>
<tr>
<td>Zero</td>
<td>Positive</td>
</tr>
<tr>
<td>Positive</td>
<td>Zero</td>
</tr>
<tr>
<td>Negative</td>
<td>Zero</td>
</tr>
<tr>
<td>Zero</td>
<td>Positive</td>
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<tr>
<td>Positive</td>
<td>Negative</td>
</tr>
<tr>
<td>Negative</td>
<td>Positive</td>
</tr>
<tr>
<td>Negative</td>
<td>Negative</td>
</tr>
</tbody>
</table>

The angle $\theta_{im}$ is the orientation of the gradient vector with respect to the $i$th half line at the $m$th pixel from the pixel of interest. However, the computation of the convergence index, $\cos \theta_{im}$ is time consuming and to reduce computation time, the orientation $\theta_{im}$ is quantized into one of eight levels, whose cosine values are tabulated. Effects of this coarse quantization are small as the number of pixels in the region of support of the COIN filter is large (typically more than several tens) and the convergence degree is given by the average of many convergence indices.

The sum of cosine of differences of angles (angles between the line connecting origin and the gradient vector of every point) will be nearly equal to 1 if it is an object region, it will be near to zero or if it will not be an object region. The filtered output is based on the directional information. The simulation results near the edges of horizontal and diagonal are shown in table 2. So the blurriness of the image is not affecting the output. The boundary of the image has identified based on the filtered output and also classified as object pixel and non-object pixel.

### 3.3. Region Grow

From the seed point calculated from the region classification and the closed contour which is derived from the active contour can be used in region growing process. The flood fill algorithm which is adopted here is a fast algorithm to grow the region. The results of this region grown output is shown in the fig 9.

### 4. EXPERIMENTAL RESULTS

The fig. 10 shows the intermediate segmentation results of sample image. Various types of cervical cancer cells are used in these experiments. For each image first the edge image has been calculated after the regional classification using K-Means algorithm. Here the k value of the image has been set as 2 or 3 depends on the output needed. If we need cell nucleolus segmentation then the k value is set as 2. Otherwise it will be set as 3. And then its corresponding gradient vector flow magnitude and angle was found. Using filtering process the image pixels are categorized and separated. The detailed algorithm is shown below

**Algorithm:**

1. get the input image
2. preprocessing - classify the input image using K-Means algorithm
3. get the seed center of the processed image
4. Find GVF and corresponding magnitude and angle
Step 5: fix the COIN filter radius and determine the kernel of the filter
Step 6: Get the filter response
Step 7: Depends on the intensity response classify the pixels into object and boundary pixels
Step 8: filling the region, based on the object boundary
Step 9: get the segmented result

The efficiency of an algorithm is measured how it can run in low end system and the speed of operation. The processing speed of the algorithm for various cancer images are shown in the table 3. The output obtained through this algorithm is compared with manually segmented output which is obtained from the Berkeley Dataset.

The execution time calculated for 2032 by 1536 dimensional cancer cell image using IDL programming with HCL machine with 512MB Ram and 1Ghz speed is shown in the table 2.

The error ratio is calculated by
\[ \text{MSE} = \Sigma (\text{Original Image} - \text{segmented image})^2 \]
\[ \text{Error} = \Sigma P(i, j) / TP + FP \]

\[ P(i, j) = \text{pixel misclassification probability} \]
\[ TP = \text{true positive} \]
\[ FP = \text{false positive} \]

The accuracy measure of this segmentation process is compared with the Berkeley Database with some natural images. The accuracy table 3 shows that by using this method we can get higher accuracy.

<table>
<thead>
<tr>
<th>Images</th>
<th>Region classification</th>
<th>Boundary image</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hsil.jpg</td>
<td>0.48</td>
<td>1.9</td>
</tr>
<tr>
<td>Hsil2.jpg</td>
<td>0.4</td>
<td>1.9</td>
</tr>
<tr>
<td>Lsil2.jpg</td>
<td>0.5</td>
<td>1.9</td>
</tr>
<tr>
<td>Lsil2.jpg</td>
<td>0.5</td>
<td>1.9</td>
</tr>
<tr>
<td>Endo2.jpg</td>
<td>0.4</td>
<td>1.9</td>
</tr>
<tr>
<td>Endo2.jpg</td>
<td>0.5</td>
<td>1.9</td>
</tr>
</tbody>
</table>

Table 3: Accuracy Compared with Manual Segmentation (Berkeley Data)

<table>
<thead>
<tr>
<th>Images</th>
<th>Segmentation accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Plane.jpg</td>
<td>96.7</td>
</tr>
<tr>
<td>Elephant.jpg</td>
<td>88.5</td>
</tr>
<tr>
<td>Eagle.jpg</td>
<td>82.2</td>
</tr>
</tbody>
</table>

The accuracy measure of this segmentation process is compared with the Berkeley Database with some natural images. The accuracy table 3 shows that this method gives higher accuracy close to that of manual segmentation.
5. CONCLUSION

This paper presents a contour based approach using magnitude and directional values to extract the object boundary from its background i.e., object segmentation. Then numbers of clusters are automatically calculated using elbow statistics. The proposed technique only requires the information of input image in gray scale form, no other assumption to be considered. This is an adaptive method without human intervention the processing is carried out. For final segmentation the result need localization process. This process can be extended with the combination of both results for multiple object detection or overlap region detection.

REFERENCES


