Using Shape Entropy as a Feature to Lesion Boundary Segmentation with Level Sets

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ABSTRACT

Accurate lesion segmentation in retinal imagery is an area of vast research. Of the many segmentation methods available very few are insensitive to topological changes on noisy surfaces. This paper presents an extension to earlier work on a novel stopping mechanism for level sets. The elementary features scheme (ELS) in [5] is extended to include shape entropy as a feature used to 'look back in time' and find the point at which the curve best fits the real object. We compare the proposed extension against the original algorithm for timing and accuracy using 50 randomly selected images of exudates with a database of clinician demarcated boundaries as ground truth. While this work is presented applied to medical imagery, it can be used for any application involving the segmentation of bright or dark blobs on noisy images.

Key Words: *Shape Special Session, Exudate Segmentation, Level Sets, Medical Image Processing.*

1 INTRODUCTION

The diagnosis of diabetic retinopathy is based upon visually recognizing various clinical features. Retinal lesions are among the first visual indicators suggestive of diabetic retinopathy. The threat to visual loss increases with the frequency of retinal lesions combined with their encroachment into the macula. To enable early diagnosis, it is necessary to identify both frequency and position of retinal lesions in relation to the fovea and other major structures (such as the optic nerve). In [5] a $lesionness$ measure was introduced and defined as a combination of perimeter size constancy shp and compactness $c = p^2/a$, where p is the perimeter and a is the area [3]. The $lesionness$ measure was the core of the stopping mechanism and upon further analysis we discovered a more direct approach by tracking the entropy of the shape of the region of interest (roi). In this work we introduce the notion of using a multivariate histogram to describe the changing shape of the roi and track the shape entropy to determine the best fit. The correlation between the change in shape entropy and the perimeter size constancy indicates the point where the curve best fits the lesion (or region of interest).

2 BACKGROUND

Retinal exudates are an interesting challenge for segmentation algorithms as they vary in appearance, conforming to one of three structures: dot exudates, fluffy exudates and circumscribed plaques of exudate. Dot exudates consist of round yellow spots lying superficially or deep in the sensory retina [9]. Exudates are usually reflective and may appear to have a rigid, multifaceted contour, ranging in color from white to yellow [1]. With varying

shapes, sizes, patterns and contrast, exudate segmentation is a demanding problem, complicated by lighting variation over the image, natural pigmentation, the intrinsic color of the lesion, and decreasing color saturation at lesion boundaries [2].

We compare our current work to the novel scheme presented in [5], along with three other well known segmentation algorithms. Sinthanayothin et al., [11], Wang et al., [12] and Osareh et al.,[6].

3 PROPOSED MODEL

3.1 Curve Propagation

For our work in lesion segmentation, level set methods provide the capability to determine not just the coarse shape of an object, but are extremely useful to tease out the fine delicate boundary fissures and curves that give a deeper look into the overall shape of a lesion candidate. From the well known definition of level sets [7]:

$$\phi_t + F_0 \left|\nabla\phi\right| + \vec{U}(x,y,t)\dot{\nabla}\phi = \varepsilon K \left|\nabla\phi\right| \tag{1}$$

where: ϕ_t is the propagating function at time t, $F_0 \left|\nabla\phi\right|$ is the motion of the curve in the direction normal to the front, $\vec{U}(x,y,t)\dot{\nabla}\phi$ is the term that moves the curve across the surface and $\varepsilon K \left|\nabla\phi\right|$ is the speed term dependent upon curvature. $\vec{U}(x,y,t)\dot{\nabla}\phi$ is the gradient map, described in section 3.2 and $\varepsilon K \left|\nabla\phi\right|$ is approximated using a central differencing scheme.

Our numerical implementation takes insights from [10]. Let ϕ_i^n be the value of ϕ at a point (pixel) i at time n. The curve evolves over a given time step thus:

$$\phi_{ij}^{n+1} = \phi_{ij}^n - \triangle t[max(-\beta_{ij},0)\triangle^+ + min(-\beta_{ij},0)\triangle^-] \tag{2}$$

where: $\beta(k) = 1 + \epsilon k$ is the velocity function, u_{ij}^n is the 'current' level set zero, $\triangle t$ is the time step (or scaling factor) and the [max...min] describes the *normal* component, and where:

$$\begin{aligned}\triangle^+ &= [max(D_x^-,0)^2 + min(D_x^+,0)^2 + max(D_y^-,0)^2 + min(D_y^+,0)^2]^{1/2} \\ \triangle^- &= [max(D_x^+,0)^2 + min(D_x^-,0)^2 + max(D_y^+,0)^2 + min(D_y^-,0)^2]^{1/2}\end{aligned} \tag{3}$$

and $D_x^-, D_x^+, D_y^-, D_y^+$ are the forward and backward difference approximations in the **x** and the **y** directions, respectively.

3.2 Gradient Map

The boundary of a lesion can be characterized by the point of strongest intensity contrast between itself and the background retina. Since retinal images are inherently noisy and the lesion edge pixels can look very much like background pixels, we want a mechanism that smooths out the noise but preserves the edges in our gradient map. Anisotropic filters address the issue of edge preservation [8]. We build our gradient map thus: $g_I(x,y) = \frac{2*(I_n)}{(2-(I_n)^2)}$ where: I_n is a histogram equalized, normalized gray-scale (green channel) image $I(x,y)$ and $\sigma = 1$.

3.3 Stopping Mechanism

A traditional use of level sets is to track a curve to an object's boundary and then stop. In our case, it is more interesting to 'peek ahead' by allowing the curve to move past the optimal boundary and then 'look back' and measure how well-formed the accumulated region is as a lesion. We have found that when the curve begins to hold its shape, or position in time, this is a potential boundary point. The curve may slow down and then subsequently speed up as its moves over a surface. It is for this reason we use the shape entropy information from one iteration to another to correlate the best stopping point with the slowing down of the curve.

3.3.1 Histogram

Our histogram model is from [4] in which the third (skewness) and fourth (kurtosis) order moments are defined for multi-dimensional surfaces. Mardia [4] defines a measure of skewness corresponding to: $\beta_{1,p} = \Sigma\Sigma S^{rr'} S^{ss'} S^{tt'} M_{111}^{(rst)} M_{111}^{(r's't')}$ where:
$S^{-1} = S^{ij}$ and $M_{111}^{(r's't')} = \frac{1}{n}\Sigma_{i=1}^{n}(X_{ri} - \bar{X}_r)(X_{si} - \bar{X}_s)(X_{ti} - \bar{X}_t)$. We modify the $M_{111}^{(r's't')}$ term to address location of pixel intensities relative to the grid to retain the true shape of the bounded object thus, $M_{111}^{(r's't')} = \frac{1}{\sum w}\Sigma_{i=1}^{n}\sum w_i(X_{ri} - \bar{X}_r)(X_{si} - \bar{X}_s)(X_{ti} - \bar{X}_t)$, where: X is a vector of x,y values, and $\overline{X}$ is a vector of the means; p is the number of dimensions ($p = 2$), w_i is the intensities at value *i*, $\sum w$ is the sum of all the intensities in the region of interest, and S^{-1} is the Covariance Matrix (inverted).

The measure of kurtosis corresponding to $B_{2,p}$ is, with our modifications:
$b_{2,p} = \frac{(\sum w)+2}{(\sum w^2)p}\sum_{i=1}^{n} w_i\{(X_i - \overline{X})' S^{-1}(X_i - \overline{X})\}^2$.

Although we do not use the values of these moments during this portion of the work, we do employ the full covariance matrix from the output of the histogram generation, and apply it to calculate entropy $H(X) = \frac{1}{2}\ln[(2\pi e)^n |det(S)|]$ where: n is the number of observations in the region of interest and S is the covariance matrix. When no discernible change is detected from one iteration to another, the curve has found its 'most informative' boundary point.

3.3.2 Best Fit Features

From the original work in [5] we are looking for measurements that can give indicators of how well-formed a region is as a candidate lesion. Thus, elementary features include 1) the number of iterations the curve held its perimeter size: shp; 2) the minimum compactness value: c; 3) the number of iterations the curve held that compactness value: chp; and 4) the gradient contrast: gc. After the curve has moved for a number of iterations (we use $P = 180$) it is possible that the curve has evolved past the optimal point describing the object boundary. Because of this possibility, the gathered measurement values are then used to 'look back in time' to find the point at which the curve best fit the object boundary.

3.3.3 Correlation

Let q be the iteration number and $h(q)$ be the count of the number of iterations for which the feature values have held up to and including q. Let q_{shp} be the iteration point where the perimeter holds its size for a $h(q) > 2$, and q_{ent} the entropy value at each successive iteration. Let q_c be the iteration with the smallest value of c, q_{gc} be the iteration with the largest contrast and q_{chp} be the iteration where c held its value the longest. Let q_μ and q_σ be the mean and standard deviation, respectively, of the iteration values for the gathered features. Let $q_{ub} = q_\mu + q_\sigma$ be the upper bound and let $q_{lb} = q_\mu - q_\sigma$ be the lower bound. Then let Z^* be the collection of features that fall within the $(one)\sigma$ boundary. Those features that fall within $(one)\sigma$ of q_μ are used to calculate the best fit point. $SV = \frac{\sum_{q \in Z^*} q}{\#Z^*}$ is the average of these bounded features, where: q is a bounded feature and $\#Z*$ is the number of bounded features. To determine the best fit point we use Pearson's product-moment coefficient correlated between the q_{shp} feature and the shape entropy q_{ent} features. $\rho_{q_{shp},q_{ent}} = \frac{E((q_{shp} - \mu_{q_{shp}})(q_{ent} - \mu_{q_{ent}}))}{\sigma_{q_{shp}}\sigma_{q_{ent}}}$ where: E is the expected value, and $\mu_{q_{ent}}$, $\sigma_{q_{shp}}$ and $\mu_{q_{shp}}$, $\sigma_{q_{ent}}$ are the first and second moments for perimeter size constancy and entropy, respectively. The images with high correlation of entropy $H(X)$ to perimeter size constancy shp use the $max(shp)$ value - the iteration where the perimeter held its size the longest. Lower correlation values require the SV calculation.

4 CONCLUSIONS

Table 1 shows the final segmentation result compared with other algorithms, and shows an increase in accuracy and decrease in error rate for the proposed model. Sensitivity values can be increased with developments to the gradient map generation. Algorithm names are as follows: ELSwE - Elementary Features Scheme w/Entropy

Correlation; ELS - Elementary Features Scheme (orig); Fuzzy - Fuzzy C-means; RRG - Recursive Region Grow; DC - Color Discriminant.

Table 1: Algorithm Performance Metrics.

Model	Sens.	Spec.	Accuracy	Error
ELSwE	96.53	99.28	99.13	22.38
ELS	96.94	98.97	98.87	29.35
Fuzzy	88.29	94.18	93.89	158.95
RRG	47.72	90.99	88.85	290.1
DC	64.67	75.77	75.21	644.75

A novel idea for automated segmentation and classification of candidate lesions using a new level set stopping mechanism has been presented. Experimental comparisons have been conducted on five segmentation approaches. All algorithms were evaluated against a randomly-selected image set with ophthalmic lesion boundary demarcation. The results shown in Table 1 demonstrate the advantage of allowing the curve propagation (region growing) to run past the optimal boundary point, thus providing a 'peek ahead' to adjacent areas. Then using gathered elementary features and correlating the strongest to shape entropy to 'look back in time' determines the best fitting curve.

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