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Superpixel Classification for Initialization in Model Based Optic Disc Segmentation

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Abstract— **Optic disc segmentation in retinal fundus image is important in ocular image analysis and computer aided diagnosis. Because of the presence of peripapillary atrophy which affects the deformation, it is important to have a good initialization in deformable model based optic disc segmentation. In this paper, a superpixel classification based method is proposed for the initialization. It uses histogram of superpixels from the contrast enhanced image as features. In the training, bootstrapping is adopted to handle the unbalanced cluster issue due to the presence of peripapillary atrophy. A self-assessment reliability score is computed to evaluate the quality of the initialization and the segmentation. The proposed method has been tested in a database of 650 images with optic disc boundaries marked by trained professionals manually. The experimental results show an mean overlapping error of 10.0% and standard deviation of 7.5% in the best scenario. The results also show an increase in overlapping error as the reliability score reduces, which justifies the effectiveness of the self-assessment. The method can be used for optic disc boundary initialization and segmentation in computer aided diagnosis system and the self-assessment can be used as an indicator of cases with large errors and thus enhance the usage of the automatic segmentation.**

I. Introduction

The optic disc (OD) is the location where ganglion cell axons exit the eye to form the optic nerve. The localization and segmentation of OD are very important in ocular image analysis and computer aided diagnosis systems of many diseases such as glaucoma. The former focuses on finding an OD pixel, very often the center of the OD [1]. The latter estimates the OD boundary. This paper focuses on the segmentation. Fig. 1 shows an example, where the line in blue indicates the OD boundaries.

Some methods have been proposed for OD segmentation, including template based methods [2][3][4], deformable model based methods [5] [6][7][8] and pixel classification based methods [9][10]. The first two types of methods are on the basis of the edge characteristics. The performance very much depends on the differentiation of edges from OD and other structures especially the peripapillary atrophy (PPA). An example of PPA is shown as the area between the blue and green lines in Fig. 1. As PPA region looks similar to OD, it is often confused to be part of OD. For example, the line in red in Fig. 1 is the boundary detected by the deformable model based method in [8]. To overcome the problem, we proposed a template based approach [4] with PPA elimination. By using a PPA detection module based on texture, the method reduces the chance of mistaking PPA as part of OD. However, the approach does not work well when PPA area is small or when the texture is not significantly predominant. Deformable models are sensitive to poor initialization. Very often, the deformation cannot exclude PPA from the segmented OD if it has been included in the initialization, possibly because of lack of significant energy terms that differentiate PPA from OD in the deformation function. However, circular Hough transform based initialization used in existing methods [6][7][8] often includes PPA as part of OD. Pixel classification methods suffer from high number of pixels, which makes optimization on the level of pixels intractable in pixel classification methods [11]. Muramatsu *et al.* [12] compared the pixel classification based methods with deformable based methods and concluded that their performance were similar and the pixel classification based methods were not very effective in differentiating PPA region from OD.

Improvement for a deformable model based OD segmentation can be done on the one hand by improving the deformation function and on the other hand by improving the initialization. In this paper, our focus is the initialization and a superpixel classification based method is proposed for OD initialization. In addition, the proposed method computes a self-assessment reliability score based on the initialization. Superpixels are local, coherent and provide a convenient primitive to compute local image features. They capture redundancy in the image and reduce the complexity of subsequent image processing tasks.

The rest of the paper is organized as follows. In Section II, we introduce the method including the generation of superpixels, the feature extraction from superpixels for the classification, the initialization of optic disc boundary and the computation of a reliability score for self-assessment. Section III shows the experimental results, followed by the conclusions in the last section.

II. Methodology

The flow chart of the proposed segmentation method is summarized in Fig. 2. The segmentation comprises: a superpixel generation step to divide the image into superpixels; a feature extraction step to compute features from superpixels; a classification step to determine each superpixel as a disc

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Fig. 1. Sample Images: blue lines are ground truth; red lines are segmented boundary; green lines are the PPA boundary.

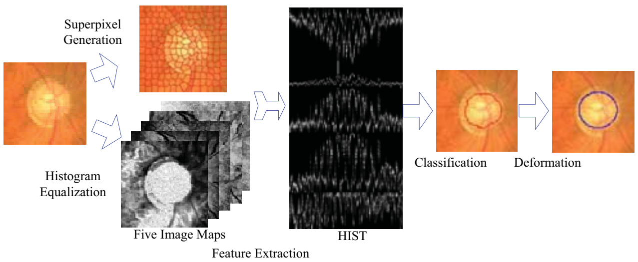


Fig. 2. superpixel Classification for Optic Disc Segmentation: Each image is divided into superpixels. The histogram from superpixels are used to classify them as disc or non-disc. The j^{th} column of HIST corresponds to the feature for j^{th} superpixel.

or non-disc pixel; an initialization and deformation step to get the optic disc boundary.

A. Superpixels

A superpixel is a perceptually consistent unit with all pixels in a superpixel close in color and texture. It reduces the complexity of images from thousands of pixels to only a few hundred superpixels. In this paper, the simple linear iterative clustering (SLIC) [13] algorithm using k-means is used to aggregate nearby pixels into superpixels whose boundaries closely match true image boundaries. Next, features from superpixels are extracted to classify them as disc or non-disc superpixels.

B. Feature Extraction

Many features can be computed from superpixels such as shape, color, location, and texture [14]. As PPA is the main challenge in OD segmentation, it is important to have a feature that differentiates PPA regions from OD regions. Since the main difference between PPA and OD is the texture, we use the histogram of each superpixel from a contrast enhanced image to map into feature space in this paper. It is motivated by the use of histogram equalization in biological neural networks [15]. By applying histogram equalization, the contrast variation from image to image is reduced. In this paper, histogram equalization is applied to r, g, and b channels respectively to enhance the images for easier analysis. This allows for areas of lower local contrast to gain a higher contrast. However, histogram equalization on r, g, b may yield dramatic changes in the image's color balance. Thus, the hue h and saturation s from HSV color space are also included to form 5 channel maps. Noted that the value channel of the HSV of a retina image does not provide additional information as it is almost the same as the red channel. The histogram of each superpixel is computed from the five channels including the histogram equalized r, g, b as well as the original h, s. In this paper, 256 bins are used in the histogram and a $256 \times 5 = 1280$ dimension feature $HIST_j$ is computed for j^{th} superpixel SP_j.

C. Superpixel Classification

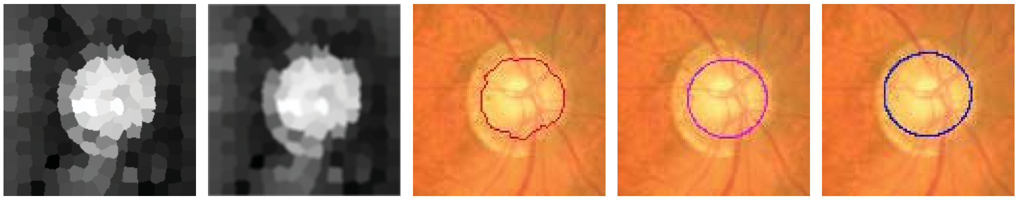
The LIBSVM [16] with linear kernel is used in our experiments. In the training, we randomly obtain a same amount of superpixels from the disc and non-disc region. One challenge to get a good classifier is that the samples from non-disc regions are often from different clusters with unbalanced numbers. One typical example is PPA. Superpixels from some PPA regions often look similar to those from optic disc. However, there are many fewer superpixels from PPA compared with other non-disc region, and the trained classifier does not have a good classification for superpixels from PPA. To overcome the problem, we adopt bootstrapping. After a classifier is obtained, examples that are misclassified are added back to the training set to train a new classifier. By iteratively adding misclassified samples, examples that are misclassified gain weight and examples that are classified correctly lose weight. We repeat the iteration until there is no improvement in the classification accuracy or the maximum iterations have been reached. After that, the trained classifier is used to classify the superpixels in testing images to get the initial boundary for deformation.

D. Initialization and deformation

A direct way to use the results from superpixel classification is to use the binary classification results from LIBSVM as the initial disc. However, some superpixels might cover pixels from both disc and non-disc region. In this paper, we use the decision values from LIBSVM. As illustrated in Fig. 3, the value for each superpixel is used as the decision values for all pixels in the superpixel. A smoothing filter is then applied to get smoothed decision values for each pixel. In our implementation, mean filter and gaussian filter are tested and the mean filter is found to work fine. The smoothed decision values are then used to obtain the binary decisions for all pixels. The largest connected object is obtained and its boundary is used as the raw estimation. The best fitted ellipse using elliptical Hough transform [4] is computed as the fitted estimation, which is used as the initial contour for deformation. In this paper, the model based optic disc segmentation in [8] is used an example to show how the initialization by superpixel classification improves the final result compared with an initialization by circular Hough transform commonly used in previous methods.

E. Self-assessment reliability score

As the OD is often an ellipse, the obtained boundary before and after fitting shall be close if the superpixel based initialization works well. Otherwise, the initialization is likely to be less reliable. Inspired by this, we propose to compute a self-assessment reliability score for the initialization. Define the set of points from the raw estimation as X and the set of points from the fitted estimation as $Y = f(X)$,



(a) (b) (c) (d) (e)

Fig. 3. Illustration of processing: (a) decision values (b) smoothed decision values (c) the raw estimation (d) the fitted estimation (e) after deformation.

	no filter	3×3	5×5	10×10	15×15
100	10.6%±8.2%	10.6%±8.0%	10.6%±8.0%	10.6%±8.0%	10.7%±8.1%
200	10.4%±7.5%	10.1%±7.5%	10.0%±7.5%	10.2%±7.5%	10.2%±7.3%
400	10.3%±7.4%	10.2%±7.2%	10.1%±7.1%	10.2%±7.4%	10.2%±7.4%

TABLE I

$\bar{E} \pm \sigma_E$ FROM TESTING IMAGES AT DIFFERENT PARAMETERS

e.g., the red and magenta lines in Fig. 3(c) and Fig.3(d), respectively. For each point x in X, we find its nearest point in Y and their distance is computed as

$$d_f(x) = \inf\{d(x,y)|y \in Y\} \quad (1)$$

where inf represents the infimum and $d(x,y)$ the Euclidean distance between x and y. Then, the self-assessment reliability score is computed as the ratio of number of x with $d_f(x) < T$ to the total number of x, i.e,

$$r(X) = \frac{Card(\{x|d_f(x) < T, x \in X\})}{Card(X)}, \quad (2)$$

where the $Card(Z)$ is the operator to get the cardinality of the set Z, and T is a threshold empirically set as five pixels in this paper.

III. Experimental Results

The ORIGA [17] database with 650 images are used here. The images are randomly divided into 163 images for training and 487 images for testing. The overlapping error E is computed as the evaluation metric.

$$E = 1 - \frac{Area(S \cap G)}{Area(S \cup G)}, \quad (3)$$

where S and G denote the segmented and the ground truth disc respectively.

There are two parameters involved: the number of superpixels and the size of filters. The first set of experiments were carried out to evaluate the performance under different parameters. Table I shows the mean overlapping error $\bar{E}$ and the standard deviation σ_E for number of superpixels at 100, 200 and 400 in combined with different filter sizes from 3×3 to 15×15 as well as the case without a filter.

To compare with previous methods, the model based approach [8] using circular Hough transform (CHT) initialization is used as the baseline. The proposed approach replaces the initialization in [8] with the results from superpixel classification. In addition, the results without histogram equalization under same framework by the proposed superpixel classification are also included to justify the effectiveness of histogram equalization. Table II shows the results. The relative reduction of overlapping error is (11.3-10.0)/11.3=11.5% compared with previous CHT initialization based method [8]. Fig. 4 shows some results by CHT initialization based method [8] and proposed method. The first row is an example without PPA where both methods work well. The second to fourth rows are examples with PPA. As we can see, the proposed method performs better.

To show the effectiveness of the self-assessment reliability score, we compute the overlapping errors for images at different range of scores. Table III shows the percentage of images in different range of scores as well as the mean and standard deviation of the overlapping errors. It shows an increase in overlapping error as reliability score reduces, which demonstrates the effectiveness of the self-assessment reliability score.

IV. Conclusions

In this paper, we propose a method for automatic OD segmentation initialization with a self-assessment reliability score. Different from previous methods, the proposed method is based on superpixel classification. Bootstrapping is adopted in the training to improve the classification accuracy. A self-assessment reliability score is computed to give assessment of the OD segmentation. The experimental results show that the proposed initialization decreases mean overlapping error from 11.3% to 10.0%, a relative reduction of 11.5% compared with circular Hough transformed based initialization. The method can be used in computer aided diagnosis system and the self-assessment can be used as indicators of cases with potential large errors and thus enhance the usage of the automatic segmentation.

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Initialization Method	$E \leq$0.1	$E \leq$0.15	$E \leq$0.2	$E \leq$0.25	$E \pm \sigma_E$
Circular Hough Transform [8]	65.7%	80.5%	85.4%	88.5%	11.3%±8.5%
w/o Histogram Equalization	65.1%	83.0%	90.8%	93.8%	10.6%±7.9%
Proposed	65.3%	84.0%	92.2%	95.1%	10.0%±7.5%

TABLE II

PERCENTAGE OF IMAGES PER E INTERVAL AS WELL AS $\bar{E}$ AND σ_E

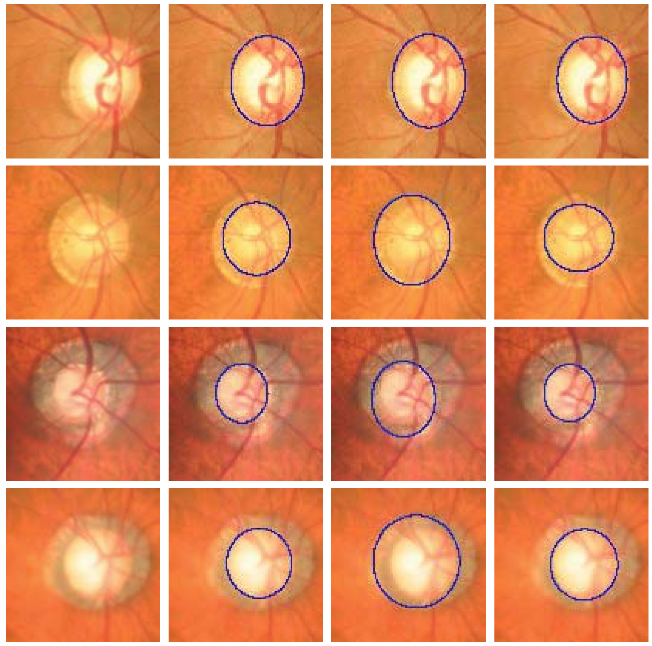

Fig. 4. Sample results. From left to right columns: the original images, the ground truth, outlines by the circular Hough transform initialization based method [8], and proposed method.

	$r \geq 0.95$	$0.95 > r \geq 0.9$	$0.9 > r \geq 0.85$	$0.85 > r \geq 0.8$	$0.8 > r \geq 0.75$	$0.75 > r \geq 0.7$	$r < 0.7$
Perc.	47.6%	21.4%	13.1%	7.2%	4.7%	2.1%	3.7%
E	8.5%	9.6%	10.0%	11.0%	14.5%	15.3%	20.4%
σ_E	5.1%	7.0%	5.2%	7.8%	8.6%	13.6%	19.9%

TABLE III

PERCENTAGE OF IMAGES, $\bar{E}$ AND σ_E PER r INTERVAL

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