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An ensembling approach for optic cup detection based on spatial heuristic analysis in retinal fundus images

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Abstract— **Optic cup detection remains a challenging task in retinal image analysis, and is of particular importance for glaucoma evaluation, where disease severity is often assessed by the size of the optic cup. In this paper, we propose spatial heuristic ensembling (SHE), an approach which aims to fuse the advantages of each method based on the specific performance in each defined sector. In this way, we generate an ensembled optic cup which is obtained from the optimal combination of the component methods. We conduct experiments on the ORIGA data set of 650 retinal images and show that the ensemble approach performs better than the individual segmentations, reducing the relative overlap error, and CDR errors by as much as 0.04 CDR units. The results are promising for the continued development of such an approach for improving optic cup segmentation.**

I. Introduction

Glaucoma is the second leading cause of blindness worldwide, and has been found to contribute to 12.4% of total blindness globally[1]. As the damage in glaucoma is permanent, vision loss in glaucoma is irrecoverable, and consequentially it is important to detect glaucoma early. In glaucoma, the optic cup is enlarged due to the death of the ganglion nerve cells, resulting in the enlargement of the optic cup relative to the optic disc, also known as the optic nerve head. Such glaucomatous damage can be observed on retinal fundus photographs, and metrics such as the cup to disc ratio (CDR) are important indicators for glaucoma risk. However, current methods of glaucoma assessment are manual and may be difficult to implement for larger scale screening programs.

Computer aided detection offers potential for the automated evaluation of retinal fundus images to assess for the risk of glaucoma. This potential has been recognized and can be seen through the various methods of optic disc detection and optic cup detection[2-6]. The detection of the optic cup remains one of the most challenging issues currently, due to the varied appearance of the optic cup. In methods which employ stereoscopic images[2-3], the detection of the optic cup is aided by the presence of depth information. In non-stereoscopic images, the lack of depth information increases the difficulty of optic cup detection. Yet non-stereoscopic cameras are more widespread and are at lower cost, which would be advantageous in screening.

We have previously developed and reported different methods of optic cup detection, comparing color-based methods and level-set based methods, with results often favouring the latter[4-6]. However, through an analysis of the individual segmentation results for each image, we found that each method can be useful at particular regions of the image, and selection of any one method based on the overall performance may not be the most optimal utilization of obtained results.

In this paper, we propose Spatial Heuristics Ensembling (SHE), a framework to combine individual segmentation results in order to improve overall segmentation performance based on the reliability and prior trends of the individual methods. In particular, we describe how SHE is used to ensemble and improve the optic cup segmentation and quantize the improvements in optic cup segmentation using experiments on a large dataset of 650 images.

II. Method

We first briefly introduce the steps involved in detecting the optic cup boundary using two previous methods. The detection of the optic cup requires first obtaining a region of interest (ROI) from the fundus image, and then determining the optic disc and cup segmentations. These candidate segmentation will be ensembled using the SHE framework to obtain the optic cup boundary.

A. ROI Detection and Optic Disc Segmentation

Constraining the focal region of analysis around the optic disc is an important step in improving the efficiency and accuracy of the optic disc and subsequent optic cup segmentations, since typically the optic disc occupies less than 15% of the fundus image. We make use of the enhanced ROI detection method previously described in [7]. The method consists of first defining a dynamically adaptable mask to remove fringing effects due to imaging artefacts occuring during the image capturing process, followed by selecting the top 0.5% of pixels based on grayscale intensity levels. The centroid of the largest cluster of these candidate pixels is used as the centre of a 800x800 pixel ROI. Next, we apply a level-set method to segment the optic disc [6], using the red channel where the optic disc contour is observed to have a higher visibility.

B. Optic Cup Segmentation

The detected optic disc boundary is used to constrain subsequent optic cup segmentation, since the optic cup lies

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within the optic disc boundary. We make use of two previously described methods in [5,6]. In the first approach, a level set (LS) method similar to that used for the optic disc is utilized. The green channel color channel is selected since it shows a higher contrast for the optic cup compared to other channels. For the second approach, we adopted a color histogram-based method (CH) which selects pixels within a certain similarity range in the red, blue and green channels to a seed point in the optic cup. Since the optic cup is typically centred on the optic disc, we estimated the seed point at the optic disc centre. Further details can be found in [5,6]. In both methods for optic cup detection, the individual cup segmentation boundaries were obtained using a direct ellipse fit of the convex envelope of the preliminary results.

C. Spatial Heuristics Ensembling

As is well-known, different segmentation methods and algorithms can differ in performance and there is no optical method for all conditions. For example, a texture-based method can work well on differentiating between grainy and smooth objects, but may perform poorer than an edge-based segmentation approach in segmenting regions in strong edges. Often, the choice of one method over another is based on statistical analysis of the overall performance results on the dataset. However, this may not be always optimal, since a particular method may have salient advantages, although it may not perform as well overall.

In this paper, a comparison of the segmentation results from each individual method for optic cup segmentation showed that although the level set approach (LS) is generally able to achieve a better overall segmentation, the color-based method (CH) was found to have a better detection of the optic cup boundary in specific regions of the optic cup.

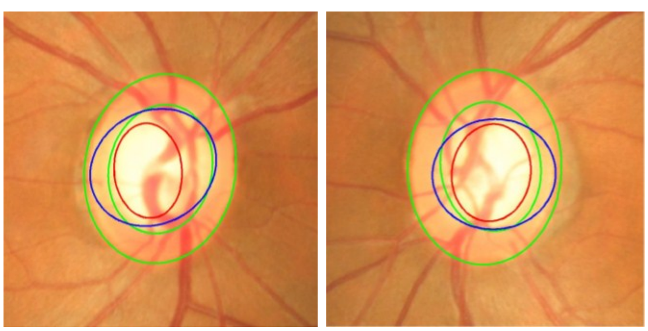

Fig. 1. Examples of various segmentations for the optic cup, showing ground truth (green), individual method using LS (blue) and CH (red)

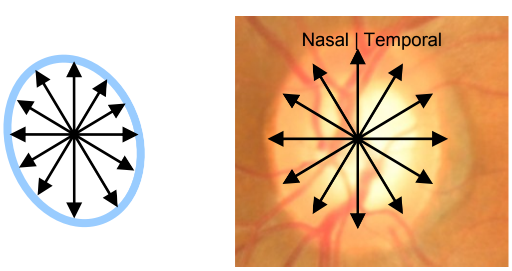

Fig. 2. Left: Rays of the set $\Theta=\{\theta^q\}$ originating and intersecting with a candidate segmentation to form the set of points $S=\{\mathbf{x}^q\}$ Right: Projection of candidate segmentation onto the coordinate system.

Fig. 1 illustrates examples of this. The level-set segmentation (LS) is represented by a blue contour, and the color-based segmentation (CH) is shown as a red contour. Ground truth for the optic cup is indicated by the green contour. In these images we follow clinical nomenclature and annotate temporal as the region towards the temple, and nasal as towards the nose, following standard clinical definitions. It can be observed in Fig. 1 that particularly in the temporal regions, the LS method tends to under-segment, extending beyond the actual optic cup boundary to the optic disc. In contrast the CH method gives a more conservative over-segmented outcome, with a better detection of the cup boundary on the temporal side. However, CH also tends to result in less accurate detection nasally. The challenge then is to determine a way to best fuse the both results.

We now propose a framework to ensemble these results through prior knowledge, or heuristics, of the reliability of each method through the respective spatial segmentation performance. This method which we term as Spatial Heuristic Ensembling (SHE) will select the best performing method at each key point of interest to optimally fuse multiple segmentation results to provide an overall segmentation which attempts to combine the advantages of each individual method. In SHE, we propose to determine the reliability of a method based on both prior performance and the current detected contour. This reliability score will help in selecting the more suitable method. Conceptually, SHE will provide a framework that incorporates knowledge of prior segmentation trends, such as the temporal undersegmentation by the LS method, and will ensemble results by taking such prior knowledge into consideration.

We first define an angular distribution model $\Theta=\{\theta_q : q=1 \ldots n\}$ for a set of n landmark angles. These angles can be equally spaced or be distributed according to a particular fixed pattern, for example to have increased point density at regions of high curvature.

Let m be the number of independent segmentation techniques tested. Each technique T generates a contour when applied on the segmentation problem. The defined angular distribution model is then applied onto this contour to obtain a set of points corresponding to each landmark angle, and obtaining a set of corresponding points $S^T=\{\mathbf{x}_q^T : q=1 \ldots n\}$ where $\mathbf{x}=(x,y)$ are image coordinates.

At each landmark θ_q, let $U_q=\{\mathbf{x}_q^v : v=1 \ldots m\}$ be the set of alternative points from the m segmentation techniques. For each landmark angle θ_q we need to determine which of the m methods in U_q is the most reliable. This can be calculated using use of Bayesian rule to formulate a probability model, although other generative or discriminative models could also be applied. For simplicity in notation, we exclude the subscript denoting the landmark angle in our following expressions.

$$P\left(\theta = \mathbf{x}^v \mid \mathbf{x}^1 \ldots \mathbf{x}^m\right) = \frac{P\left(\theta = \mathbf{x}^v\right) \cdot P\left(\mathbf{x}^1 \ldots \mathbf{x}^m \mid \theta = \mathbf{x}^v\right)}{\sum_{j=1}^{m} P\left(\theta = \mathbf{x}^j\right) \cdot P\left(\mathbf{x}^1 \ldots \mathbf{x}^m \mid \theta = \mathbf{x}^j\right)} \quad (1)$$

We assume conditional independence for each technique, since each technique employs different approaches for cup segmentation. The expression can then be simplified to

$$P\left(\theta = \mathbf{x}^v \mid \mathbf{x}^1 \ldots \mathbf{x}^m\right) = \frac{P\left(\theta = \mathbf{x}^v\right) \cdot \prod_{j=1}^{m} P\left(\mathbf{x}^j \mid \theta = \mathbf{x}^v\right)}{\sum_{j=1}^{m} P\left(\theta = \mathbf{x}^j\right) \cdot P\left(\mathbf{x}^1 \ldots \mathbf{x}^m \mid \theta = \mathbf{x}^j\right)} \quad (2)$$

and further as

$$P\left(\theta = \mathbf{x}^v \mid \mathbf{x}^1 \ldots \mathbf{x}^m\right) \propto P\left(\theta = \mathbf{x}^v\right) \cdot \prod_{j=1}^{m} P\left(\mathbf{x}^j \mid \theta = \mathbf{x}^v\right) \quad (3)$$

At each q-th point, the most suitable method is selected through the maximum a posteriori (MAP) approach, or selecting the outcome with the largest reliability score

$$\hat{\mathbf{x}} = \arg\max_{v} P\left(\theta = \mathbf{x}^v\right) \cdot \prod_{j=1}^{m} P\left(\mathbf{x}^j \mid \theta = \mathbf{x}^v\right) \quad (4)$$

This naïve Bayesian classifier approach is used to determine the selected technique at each of the n landmarks. Using such an approach at each θ_q angle, an ensemble set of points $\hat{S} = \left\{\hat{\mathbf{x}}_q : q = 1 \ldots n\right\}$ is obtained from the m methods under consideration. It should be noted that different Bayesian models are used for each θ_q as each region can have different characteristics which can be favourable to different segmentation techniques.

Training. The SHE implementation in our paper is trained in the following way. For a given image, the angular distribution model $\Theta = \left\{\theta_q : q = 1 \ldots n\right\}$ is applied onto the ground truth reference contour *GT* and contours from m independent techniques. In this way, we obtain a ground truth point distribution $S^{GT} = \left\{\mathbf{x}_q^{GT} : q = 1 \ldots n\right\}$ and point distributions for each of the m independent techniques $S^m = \left\{\mathbf{x}_q^m : q = 1 \ldots n\right\}$. We consider the m points at each angle θ_q and classify the technique corresponding to the point with the minimum l_2 norm as the "correct" point i.e.

$$\arg\min_{v} \left|\mathbf{x}_q^{GT} - \mathbf{x}_q^v\right|$$

This process is repeated for all the q angles to obtain and train classifiers at each angle q.

D. SHE for optic cup segmentation

We use the proposed SHE framework to detect the optic cup by fusing LS and CH. For the implementation used in this paper, we defined equal intervals of $\Delta\theta = \pi/6$, centered on the optic disc. We take the polar system of coordinates with reference to the right eye, where the temporal region is at θ = 0 rad. In order to maintain a consistent system of reference, left eye images are horizontally flipped. The classification of left or right eye fundus image was based on the method we previously developed [8]. An illustration of the coordinate system of reference is shown in Figure 2. To obtain the fused cup boundary, we fitted the ensembled set of points $\hat{\Theta} = \left\{\hat{\theta}_q : q = 1 \ldots n\right\}$ using direct ellipse fitting [9].

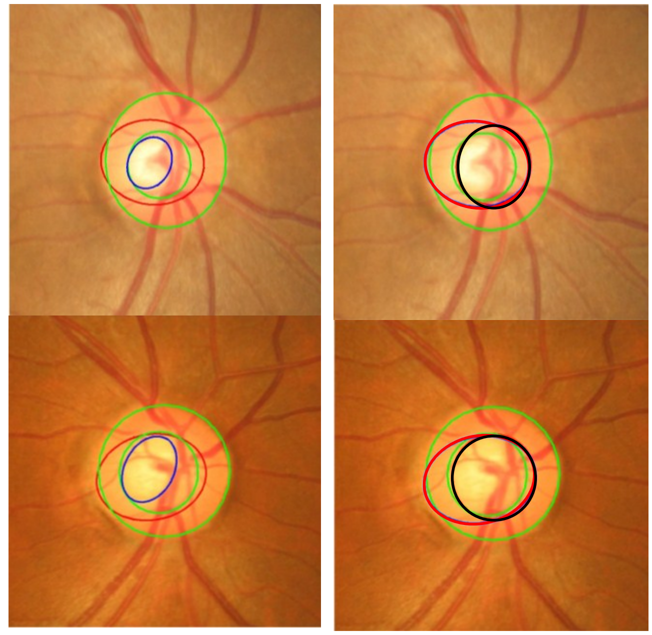

Fig 3. Examples of SHE-aided segmentation for the optic cup, showing the ground truth cup in green. Left image shows the candidate segmentations with CH in blue and LS in red. Right image shows the ensembled cup in black, with LS also shown.

III. Experiments and Results

We utilized 650 retinal fundus photographs images from the ORIGA-light database [10] to evaluate the utility of the proposed ensembling approach. The photographs were digitally captured using a 45° FOV Canon CR-DGi retinal fundus camera with a 10D SLR backing under clinical conditions, with each image having an image resolution of 3072x2048 pixels. A team of graders manually assessed and agreed upon the optic cup and optic disc boundaries, and this is taken as the ground truth segmentation. In addition, these images were also processed using our previous methods based on level-set (LS) and color (CH).

We equally split the images into two sets, ORIGA1 and ORIGA2, which we alternate as training and test sets to estimate the parameters for the Bayesian models. These parameters were then used in the proposed SHE framework. We performed resubstitution testing by running the training set through the SHE framework, following which the test set was then processed to obtain the SHE cup segmentations.

TABLE I

COMPARISON OF OPTIC CUP SEGMENTATION

	Metrics		
	m_1 (%)	$\Delta VCDR$	$\Delta HCDR$
Training: ORIGA1			
Test:			
ORIGA1	40.1 (18.3)	0.14 (0.14)	0.14 (0.13)
ORIGA2	40.9 (18.0)	0.15 (0.13)	0.16 (0.13)
Overall	40.5 (18.2)	0.14 (0.13)	0.15 (0.13)
Training: ORIGA2			
Test:			
ORIGA1	40.3 (18.2)	0.15 (0.14)	0.15 (0.13)
ORIGA2	41.0 (18.2)	0.15 (0.13)	0.16 (0.13)
Overall	40.7 (18.2)	0.15 (0.14)	0.15 (0.13)
SHE-overall	40.6 (18.2)	0.14 (0.13)	0.15 (0.13)
LS	47.7 (17.6)	0.16 (0.14)	0.17 (0.14)
CH	47.9 (16.6)	0.15 (0.13)	0.19 (0.13)

Numbers indicate means, numbers in brackets are the associated standard deviations.

Examples of the individual segmentations and SHE optic cup are shown in Fig. 3.

To quantitatively assess the performance of the SHE framework in comparison with the individual CH and LS methods, we utilized four metrics, where A refers to the obtained segmentation result and GT refers to the ground truth segmentation: (1) relative overlap error $m_1 = [1-(A \cap GT / A \cup GT)] \times 100\%$; (2) Vertical cup to disc ratio difference $\Delta VCDR = VCDR_A - VCDR_{GT}$; and (3) Horizontal cup to disc ratio difference $\Delta HCDR = HCDR_A - HCDR_{GT}$. The vertical (V) or horizontal (H) cup to disc ratio is defined as the ratio of the maximum vertical or horizontal optic cup dimension against the corresponding optic disc dimension. The cup to disc ratio (CDR) is an important indicator of risk for glaucoma since a larger is associated with the glaucomatous optic nerve damage. To compare the performance of the optic cup dimensions using the proposed SHE framework and individual methods, we use the ground truth optic disc dimensions for all CDR calculations. The experimental results are presented in Table I.

From the results, it can be observed that the results are relatively consistent when the training set is changed from ORIGA1 to ORIGA2. The overall cross-validation performance is also shown for the SHE framework. The results show that the use of the SHE framework has reduced the lower overlap error by 7% over the individual LS or CH methods. Further, this reduced overlap error is due to a reduction in the error in the cup width, as shown by the larger improvement in $\Delta HCDR$, with an average improvement of 0.04 and 0.02 over the individual CH and LS methods respectively.

IV. CONCLUSIONS

Determining the optic cup is an important task in the detection of glaucoma. Different methods can be used to detect the optic cup, which each method offering various advantages. In this paper, we have proposed a framework for the spatial heuristic ensembling (SHE) of results from different segmentation methods to fuse the advantages of each. Experimental results show that the SHE-derived optic cup is closer to the ground truth than the individual component methods. The results are promising for further development to extend and further development SHE framework for use improving the optic cup boundary in automatic glaucoma detection. Although we describe the fusion of two methods in this paper, the method can intuitively be extended to include multiple methods as well.

REFERENCES

[1] D. Pascolini, S. P. Mariotti, G. P. Pokharel, R. Pararajasegaram, D. Etya'ale, A. D. Negrel, and S. Resnikoff, "2002 global update of available data on visual impairment: a compilation of population based prevalence studies," *Ophthalmic Epidemiol*, vol. 11, 67-115, Apr 2004.

[2] M.D. Abramoff, W.L.M. Alward, E.C.Greenlee, L. Shuba, C.Y. Kim,J.H. Fingert, Y.H. Kwon, "Automated Segmentation of the Optic Disc from Stereo Color Photographs Using Physiologically Plausible Features," *Invest. Ophth. Vis. Sci*. vol. 48, 1665-1673, April 2007.

[3] J. Xu, O. Chutatape, E. Sung, C. Zheng, P.C.T. Kuan, "Optic disk feature extraction via modified deformable model technique for glaucoma analysis," *Pattern Recognition*, vol. 40, 2063-2076, July 2007

[4] Y. Hatanaka, A. Noudo, C. Muramatsu, A. Sawada, T. Hara, T. Yamamoto, and H. Fujita, "Vertical cupto-disc ratio measurement for diagnosis of glaucoma on fundus images", Proc. SPIE 7624, 76243C (2010).

[5] J. Liu, D. W. K. Wong, J.H. Lim, X. Jia, F. Yin, H. Li, W. Xiong, T.Y. Wong, "Optic cup and disk extraction from retinal fundus images for determination of cup-to-disc ratio," *Conf Proc IEEE ICIEA,* 1828-1832, 2008.

[6] D. W. K. Wong, J. Liu, J.H. Lim, X. Jia, F. Yin, H. Li, T.Y. Wong, "Level-set based automatic cup-to-disc ratio determination using retinal fundus images in ARGALI," *Conf Proc IEEE Eng Med Biol Soc*., 2266-2269, 2008.

[7] Z. Zhang; B.H. Lee; J. Liu; D.W.K. Wong; N.M. Tan; J.H. Lim; F. Yin; W. Huang; H. Li; T.Y. Wong; , "Optic disc region of interest localization in fundus image for Glaucoma detection in ARGALI," *Conf Proc Industrial Electronics and Applications (ICIEA*), pp.1686-1689, 15-17 June 2010.

[8] N.M. Tan, J. Liu, D.W.K. Wong, Z. Zhang, S. Lu, J.H. Lim, H. Li, T.Y. Wong, "Classification of left and right eye retinal images," *Medical Imaging 2010: Computer-Aided Diagnosis. Proceedings of the SPIE,* Volume 7624, pp. 762438-762438-8 (2010).

[9] Fitzgibbon, A.; Pilu, M.; Fisher, R.B.; , "Direct least square fitting of ellipses," Pattern Analysis and Machine Intelligence, IEEE Transactions on , vol.21, no.5, pp.476-480, May 1999

[10] Z. Zhang; F. Yin; J. Liu; D.W.K. Wong; N.M. Tan; B.H. Lee; J. Cheng; T. Y. Wong; , "ORIGA-light: An online retinal fundus image database for glaucoma analysis and research," *Conf Proc IEEE Eng Med Biol Soc*., pp.3065-3068, Aug. 31 2010-Sept. 4 2010.