Texture Analysis for the Segmentation of Optic Disc in Retinal Images

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***Abstract*—This paper describes ongoing work on the segmentation of the optic disc in retinal images using pixel classification and circular template matching. The pixel property used for classification is based on texture. Two texture measurements were used, Binary Robust Independent Elementary Features (BRIEF) and a rotation invariant BRIEF (OBRIEF). This texture measurement is chosen because it can address the illumination issues of the retinal images and has a lower degree of computational complexity than most of the existing texture measurement methods currently used in the literature. The method was tested on a set of 196 images composed of 110 healthy retina images and 86 glaucomatous images. The average mean overlapping ratio between the true optic disc region and the segmented region is 0.81 and 0.82 for BRIEF and OBRIEF respectively. Comparison with a method based on the Hough Transform and Snake is also provided.**

***Index Terms*—Optic disc segmentation, Texture, BRIEF**

I. INTRODUCTION

Texture analysis is important in many applications of computer image analysis, either for the purpose of classification or segmentation of images. It has been used in many applications such as biomedical image analysis, face analysis, industrial surface inspection and content based image retrieval. As a result, much research has focused on deriving powerful and efficient texture descriptors. Some of these texture descriptors are based on properties derived from spatial distributions of image gray levels such as Grey Level Co-occurrence matrices (GLCM) [1] and Local Binary Pattern (LBP) [2] and some are based on structural approaches, such as by defining texture using geometrical placement rules of unit patterns (textons) [3]. Others make use of model based approaches, such as in Gaussian Markov random fields [4] or rely on the extraction of the response to a scale space filter such as wavelet analysis [5].

A good texture descriptor is said to have a balance between two competing goals; high quality description and low computational requirements. High quality description means robust performance regardless of the variations present in the image. These variations may include changes in orientation, scale and illumination. Of course a texture descriptor which is robust to all the above variants is yet to be defined, however there are a few notable texture descriptors in the literature which are invariant to one or more of these changes. One of them is a texture descriptor based on Binary Robust Independent Elementary Features (BRIEF) [6], which is invariant to image illumination as well as having quite a low computational requirement compared to other texture descriptors currently used.

This paper is focused on ongoing work on the segmentation of the optic disc in a retinal image. Three of the main problems which make optic disc segmentation difficult are (1) ingoing and outgoing blood vessels obscure part of the optic disc boundary, (2) the variable contrast around the optic disc and (3) the illumination of the retina image is not uniform. This uneven illumination will have an influence on the subsequent statistical analysis. As a result most of the previous methods need to do some pre-processing steps prior to the optic disc segmentation process. These pre-processing steps may include blood vessel removal and in painting to suppress the blood vessel influence; and illumination correction to correct the non uniform illumination and improve the contrast.

In an attempt to cater for these three problems, our method combines pixel classification and circular template matching to segment the optic disc. For the pixel classification, we use BRIEF which is inherently invariant to image illumination. We also make use of a machine learning approach. We take training data from the optic disc and background and use it to train a classifier to recognize these two classes. This way we can exploit the knowledge of the characteristics of the optic disc in the segmentation process. In addition, since the optic disc boundary is circular in nature while the retinal blood vessels are oriented more randomly we proposed another texture measurement, a rotation invariant BRIEF (OBRIEF). The use of OBRIEF is an attempt to reduce the misclassification of blood vessel boundary pixels as optic disc pixels. The circular template matching is to obtain a circular approximation of the optic disc. This will bridge the gaps caused by ingoing and outgoing blood vessels near the optic disc boundary and will approximate the optic disc boundary if not all of the optic disc boundary is detected.

We validate our result with a retina image dataset consisting of both normal and glaucomatous images. A comparison with other optic disc segmentations based on the Hough Transform and deformable contour or snake is also provided.

II. LITERATURE REVIEW

Recently localization and segmentation of the optic disc has been investigated extensively. There are many reasons why this is so. The optic disc can be used as a landmark for normalizing

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the image, that is to bring the retinal image to a standard orientation and possibly size. It can also be used as a point of reference for identification of other retinal structures such as the fovea. In addition the optic disc is very important for glaucoma diagnosis and monitoring.

Glaucoma is a disease of the eye which may cause blindness if not treated correctly. Since this disease is asymptomatic in nature, early detection is preferable. Current methods based on fundus image are by measuring the vertical cup to disc ratio (CDR), observing the retinal rim thinning and confirming that the ISNT rule is obeyed [7]. All these methods require the identification of the optic disc boundary. Thus optic disc segmentation is a fundamental and essential step to automate the detection of glaucoma.

Several methods have been proposed for optic disc segmentation. The deformable contour or snake has been used in [8], [9], [10]. This method attempts to capture the optic disc boundary as accurately as possible. There are two types of deformable models used for optic disc segmentation: (1) region based and (2) gradient-based. Region based active contour models make use of statistical information from the background and foreground regions [8]. The initial contour can either be placed manually or automatically. The energy function is minimised to best separate these two regions. In the case where the object to be segmented cannot be distinguished in terms of a global statistic, other information such as using integrated information from multiple image channels can be used [8].

In gradient based deformable models, the contour is deformed under the influence of the energy term defined by the image gradient. The presence of the blood vessels passing in and out of the optic disc boundary and atrophy may prevent the snake from evolving to the true optic disc boundary correctly. Because of this, pre-processing is often implemented prior to snake implementation e.g blood vessel removal through morphological filtering as in [9] or histogram equalization followed by thresholding and pyramid edge detection to enhance the edge [10]. Other than the blood vessel's influence, gradient based snake performance also performs poorly in images with not so favourable image contrast, especially if this is around the optic disc boundary [11]. For this type of image, optic disc approximation using circular or elliptical template matching may give a better segmentation result.

In circular or elliptical template matching, the matching can be performed on an edge map extracted from the underlying image. The optic disc boundary found through this method is an approximation and may sometimes not be as precise as the boundary obtained by deformable contours. Hough Transform [9], [11], [12] and ellipse fitting [13] are some of the template matching techniques successfully applied for optic disc segmentation.

An alternative method for optic disc segmentation is using pixel classification. Pixel classification is where every pixel in the retina image is classified into a class, such as optic disc or background. It uses multiple pixel features which may include pixel texture, intensity, contrast of the surrounding regions, proximity to the edge and so forth. Fuzzy C Means (FCM) and Aritificial Neural Networks (ANN) are used in [14] to classify image pixels as optic disc or background. A method based on the snake was also implemented. Comparison among the three approaches shows that pixel classification is able to demonstrate comparable performance to the snake approach.

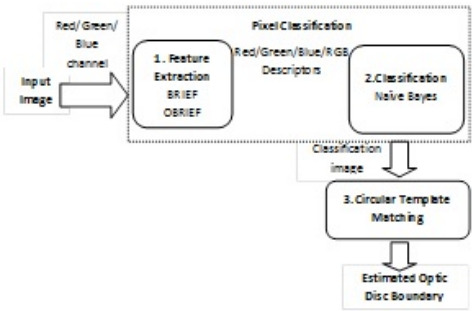

Fig. 1. Flow Chart of the method

In this work we implement a pixel classification method followed by circular template matching to segment the optic disc. This work differs to the previous pixel classification works in that we use pixel's features based on texture, BRIEF and OBRIEF, which are inherently invariant to image illumination. In doing so we avoid the pre-processing steps often implemented in other methods. Furthermore OBRIEF is rotation invariant, this will reduce the misclassification of blood vessel boundary as optic disc pixels.

III. METHOD

The procedure is illustrated in Fig. 1 and consists of 3 main steps:

1) *Feature Extraction:* Each pixel from each colour (red, green and blue) channel is transformed into its BRIEF/OBRIEF representations or descriptors. In addition to all the three channels, to ensure that we utilize the available colour information in the retina image, we also combine the BRIEF/OBRIEF descriptor from those separate channels into an RGB descriptor. To form the RGB descriptor, each descriptor from each channel is concatenated into a single binary string. For example assuming a 16 bits descriptor is used to represent a region in each colour channel, then the resulting descriptor for that pixel in the RGB channel is 48 bits length. The first 16 bits will be from the red channel, second 16 bits from the green channel and then another 16 bits from the blue channel. These representations are then used for classification
2) *Classification:* Nave Bayes is the selected classifier used to classify each pixel into one of two classes :'optic disc' and 'background'.
3) *Circular template matching:* This last stage is to obtain the final circular approximation of the optic disc.

A. Binary Robust Independent Elementary Feature (BRIEF)

The original version of BRIEF takes a smoothed image patch and computes the result of the binary test between pair

of pixels intensities. The feature descriptor for a patch is then defined as a vector of n binary test points. The location of the pixels can be randomly selected or pre-defined (for supervised learning) and lies within the patch. There is a concern that the use of smoothing may alter the image spatial details thus, the used of a threshold value when calculating the BRIEF descriptor is proposed in [15] and used in this work. The formal definition is as follows:
A test τ defined on patch p of size SxS as

$$\tau(p; \underline{x}, \underline{y}) = \begin{cases} 1 & \text{if (p(}\underline{x}\text{) - p(}\underline{y}\text{)) >Threshold} \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

where $p(\underline{x})$ and $p(\underline{y})$ are the pixel intensities at location $\underline{x}$ and $\underline{y}$.

The BRIEF descriptor is then defined as the n bit vector:

$$f_n = \sum_{1 \leq i \leq n} 2^{i-1} \tau(p; \underline{x}_i, \underline{y}_i) \quad (2)$$

We choose $S = 27$ and $n = 16$. Other combinations of S and n were tested with smaller number of training cases and the above mentioned parameters were selected as they gave the best result. The threshold is set to 3 times the estimated image's noise magnitude.

B. Rotation Invariant BRIEF

We obtain the OBRIEF in the following steps:

1) The centre of the optic disc is estimated. For this purpose we use the centre of gravity of the image. Sometimes the centre of gravity does not necessarily return a point at the centre, but we found that as long as the detected point is within the optic disc, it is acceptable.
2) For each pixel, we identify the direction (α) with respect to the estimated optic disc centre. This is to allow for orientation-normalized descriptors and hence achieve the rotation invariance.
3) Then a set of point pairs are collected from the SxS image patch centred on the pixel of interest and in a rotated pattern.
4) The bit vector n_d is assembled by performing the intensity comparisons of the point pairs (i.e. in rotated pattern). Thus for each bit:

$$b = \begin{cases} 1 & (P(\underline{x})^{\alpha} - P(\underline{y})^{\alpha}) \text{>Threshold} \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

The value of S, n_d and threshold used are the same as the ones used in BRIEF, described earlier.

C. Naive Bayes

For the texture pixel classification we employ a two fold cross validation approach using Naive Bayes[16] as the classifier.Since the BRIEF features are binary, given a finite set of features then Bayes theorem can be expressed as below:

$$P(\omega_i|x) = \frac{P(x|\omega_i)P(\omega_i)}{P(x)} \quad (4)$$

Fig. 2. Samples of the templates used

Where ω_i is the ith class. $P(\omega_i)$ is the priori probability of class ω_i, $P(x|\omega_i)$ is the likelihood of feature vector x given a class ω_i and $P(\omega_i|x)$ is the posterior probability of class ω_i given observation x, i.e. the result of the Bayes rule. $P(x)$ is the normalization constant. We estimate $P(\omega_i)$ and $P(x|\omega_i)$ from the training data. The decision rule used for classification is based on maximum a posterior (MAP), i.e. choose the class with the highest $P(\omega_i|x)$.

D. Circular template Matching

The template matching is a technique that attempts to answer a variant of the following question: Does an image contain some of the features of the template image and if so, where? Some form of similarity measure is used to indicate a match between template and image at a particular position. And if the similarity measure is large enough then the object can be assumed to be present at that position. Several similarity measures are possible, and one of them is cross-correlation, which can be efficiently implemented in the fourier transform domain. Circular and elliptical templates are used to approximate the circular boundary of the optic disc. The templates used are of various diameters and orientations (see examples in Fig. 2), and these templates will be cross correlated with the classification result images. The matching process is done in parallel in the four classification images from the red, green blue and RGB data. The highest correlation coefficient value is used to indicate a match.

IV. TESTING AND RESULTS

The image database used in this study is made up of 196 images. 110 images are normal and 86 are glaucomatous images kindly provided by Manchester Royal Eye Hospital. Two evaluation performances were performed to evaluate the proposed approach. First we compared the two texture measurements (BRIEF and OBRIEF) on the basis of retinal image texture classification. The retina textures that we have differentiated are the background and optic disc. The second experiment was carried out to evaluate the performance of the proposed method for automatic segmentation of optic disc.

A. BRIEF vs OBRIEF

We used classification error rate to compare the performance of the two texture descriptors. This is because our particular concern is on minimizing the influence of the blood vessel. The classification error rate is the percent of incorrect classification and is calculated as:

$$Error = \frac{FN + FN}{TP + TN + FP + FN} \quad (5)$$

Where TN is true negative, TP is true positive, FP is false positive and FN is false negative.

Table I shows the average classification error rate based on the two texture measurements. For both sets of images (glaucomatous and normal), the lowest average error rate is obtained using OBRIEF in the green channel with 18.5 % while the average lowest error rate across all channel is 20 %. By using BRIEF, the average error rate across all channel is 27 % and the lowest also in green channel with 18.5 %.

In this work, we obtain a rather high value of classification error rate. Two reasons may be the cause of this. The first is the misclassification of pixels inside the optic disc as background pixels. As can be seen from Fig.3, the classifier correctly classifies the pixels near the optic disc and cup boundary and near the blood vessels inside the optic disc as the optic disc pixels, however pixels in the smooth region inside the optic disc are often misclassified as background. This may be because BRIEF/OBRIEF descriptors on smooth regions inside the optic disc are mostly zeroes, similar to the value of the BRIEF/OBRIEF descriptors obtained in the background. As a result, this group of pixels is often misclassified as background. Furthermore the areas near the boundary contain more textural information compared to a smooth region inside the optic disc. Thus these regions may represent sets of unique descriptors that are differentiable from the background descriptors.

The second reason is the misclassification of vessel boundary in the background as optic disc pixels. Although the use of OBRIEF manages to reduce this misclassification by 7 % (refer to Fig. 3 for some examples) but in a few isolated cases, this misclassification still occurs. Further post-processing may be required and this will be considered in our future work. Nevertheless this result confirms our earlier assumption that OBRIEF is better at differentiating between optic disc boundary and blood vessel boundary compared to BRIEF.

TABLE I
AVERAGE CLASSIFICATION ERROR RATE OF THE TWO TEXTURE MEASUREMENT

		Average classification error rate				
		Red	Green	Blue	Color	Average
OBRIEF	Normal	20	18	20	22	20
	Glaucoma	19	19	20	22	20
	All	**19.5**	**18.5**	**20**	**22**	**20**
BRIEF	Normal	24	30	23	31	27
	Glaucoma	27	26	27	30	27.5
	All	**25.5**	**28**	**25**	**30.5**	**27.25**

B. Optic Disc Segmentation

For the optic disc segmentation, the evaluation used is based on the overlapping area (S) between the ground truth optic disc regions and the approximated regions obtained from the described approach. The value '1' indicates perfect match between ground truth and the approach. The overlapping area is defined as:

$$S = \frac{Area(G \cap E)}{Area(G \cup E)} \tag{6}$$

The result is given in Table II. As can be seen from the table, both methods show a comparable performance in the segmentation of the optic disc. Samples of the segmented optic disc are shown in Fig. 3. Both methods prove to be reliable in segmenting the optic disc especially in an image with good contrast around the optic disc boundary and where the blood vessels are not very thick (Fig. 3: Row 1). In an image with low and variable contrast around the optic disc boundary and large central blood vessels OBRIEF performed better (Fig. 3: Row 2). This is because the major vessel's influence is minimal in this image.

Poor performance is observed in images with the presence of severe peripapillary atrophy especially when the optic disc boundary is completely missing (Fig. 3: Row 3). The atrophy region has almost similar characteristics to the optic disc. Therefore the pixels belonging to atrophy regions were often misclassified as part of the optic disc. In this type of image, the optic disc will be over segmented or under segmented. In the case of mild atrophy, this approach is sometimes able to provide good segmentations as can be seen in Fig. 3:Row 4.

The average overlapping score result in the glaucomatous set is slightly lower than the normal set. The reason is that glaucoma deforms the optic disc shape making it less conforming to the shape of our templates. Furthermore, the number of images affected by atrophy is larger in this set compared to normal sets. Overall there are 36 images of mild to severe atrophy in this dataset.

TABLE II
DISC SEGMENTATION RESULT FOR BRIEF AND OBRIEF

	Average Overlapping Score	
	OBRIEF	BRIEF
Normal	0.85	0.84
Glaucoma	0.79	0.77
All	0.82	0.81

C. Comparison with other methods

A quantitative comparison with two other methods was also conducted. They are the Canny edge detector followed by the Hough Transform and deformable contour or snake as implemented in [9]. The initial snake placement is based on the Hough transform result and blood vessels are removed prior to the snake implementation. These two methods were tested with the same database as before.

The evaluation used in their work is based on calculating the discrepancy between two closed boundary curves or contour described as:

$$D(G_c, S_c) = \frac{\frac{1}{2}\{\frac{1}{n}\sum_{i=1}^{n} d(g_c i, S) + \frac{1}{m}\sum_{i=1}^{m} d(s_c i, G)\}}{G_d} \tag{7}$$

G_c and S_c are the contours of the segmented area in the ground truth and segmented images. $d(a_i, B)$ is the minimum distance from point i on the contour A to any point on the contour B. G_d is the diameter of the ground truth contour. A low

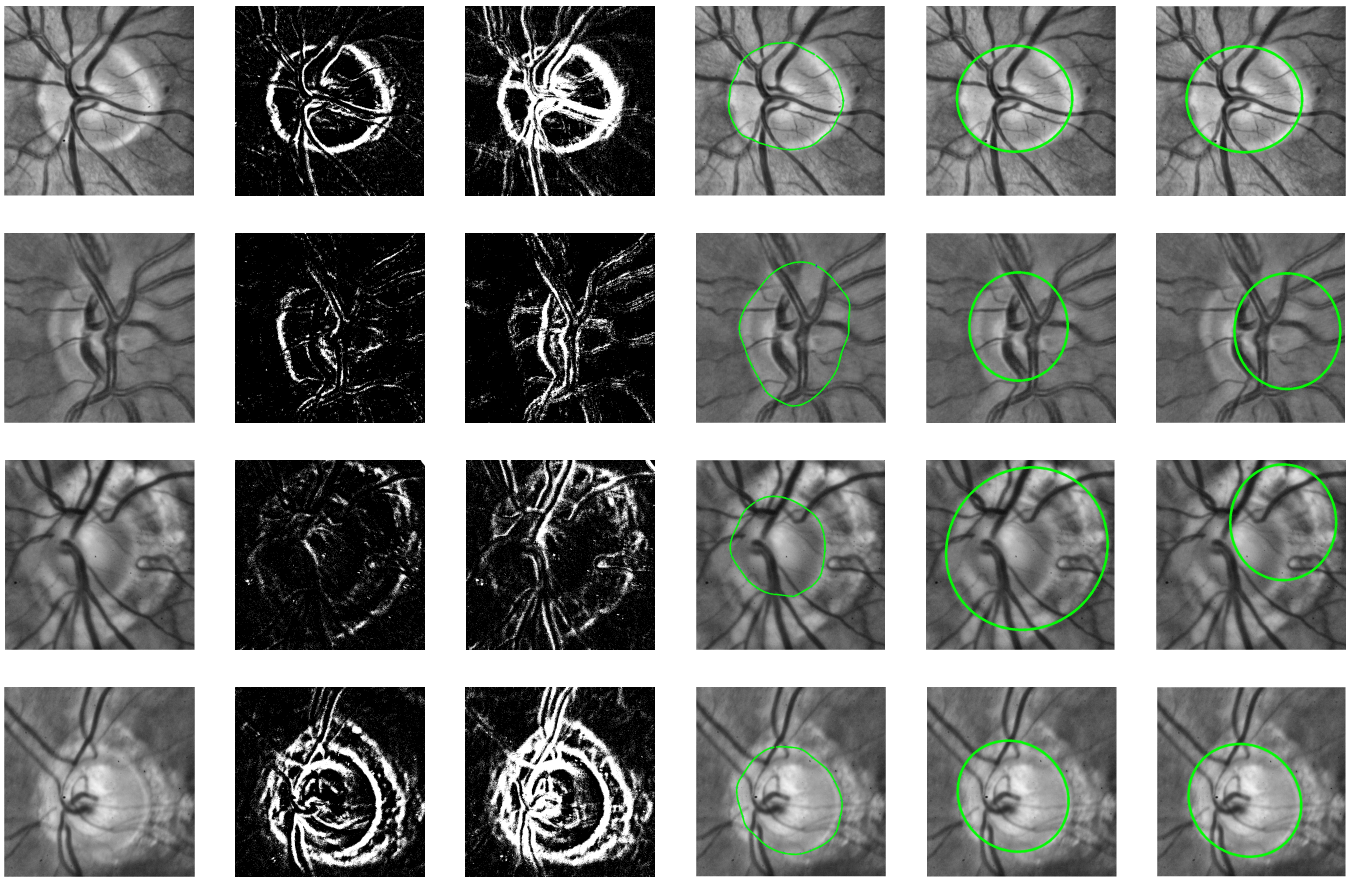

Fig. 3. Figure 3: Comparison of the disc outlines determined by the two methods. Row 1- 4: example of an image with good contrast, image with low variable contrast around the optic disc boundary, image with severe papillary atrophy and image with mild atrophy, respectively. From left to right columns: original image, pixel classification using OBRIEF, pixel classification using BRIEF, image with the ground truth, the approximated boundary based on OBRIEF and approximated boundary based on BRIEF.

discrepancy value implies a better segmentation performance. The comparison result is shown in Table III. As can be seen from the Table, our approach shows improvement in minimizing the discrepancy over the Hough Transform and the snake method.

TABLE III
DISC SEGMENTATION RESULT FOR BRIEF AND OBRIEF

	Mean Discrepancy			
	OBRIEF	BRIEF	Hough Transform	Snake
Normal	0.06	0.06	0.10	0.13
Glaucoma	0.09	0.09	0.13	0.16
All	0.08	0.08	0.12	0.15

V. CONCLUSION AND FUTURE WORK

A method for optic disc segmentation is presented in this paper. We demonstrate that the proposed method is at least as reliable as other algorithms for the optic disc segmentation with the advantages of computational simplicity. An interesting property of our method is the use of illumination invariance texture measurement to address the illumination issue of the retina images. Furthermore, by making use of machine learning technique in one our approaches, we can exploit the knowledge of the characteristics of the optic disc in the segmentation process.

Nonetheless, the method has several limitations which we wish to address in future research. The approach often gives unsatisfactory segmentation results in the presence of severe atrophy. This may be due to misclassification of atrophy pixels as optic disc pixels. In the future, we intend to ensure that pixels used for training the classifier have sufficient number of atrophy pixels so that the result may improve. At the moment the pixels used in the training data were randomly selected. Another option is to train the atrophy pixels and classify it as a separate class. Whether this stage is to be implemented after or before the optic segmentation is still under consideration.

Other than due to severe atrophy, the approach often fails to obtain a good segmentation in the case where the optic disc is not the 'standard' shape such as when the optic disc has an exceptional degree of ellipsity. Therefore we are currently looking at ways to trace the optic boundary from the classification result image guided by the obtained circumference given by our template matching approach.

REFERENCES

[1] R. M. Haralick, K. Shanmugam, and I. H. Dinstein, "Textural features for image classification," *IEEE Transactions on Systems, Man and Cybernetics*, no. 6, pp. 610–621, 1973.

[2] T. Ojala, M. Pietikainen, and T. Maenpaa, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," *IEEE Transcations on Pattern Analysis and Machine Intelligence*, vol. 24, no. 7, pp. 971–987, 2002.

[3] T. Randen and J. H. Husoy, "Filtering for texture classification: A comparative study," *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, vol. 21, no. 4, pp. 291–310, 1999.

[4] R. Hu and M. M. Fahmy, "Texture segmentation based on a hierarchical markov random field model," *Signal processing*, vol. 26, no. 3, pp. 285–305, 1992.

[5] M. F. A. Fauzi and P. H. Lewis, "A multiscale approach to texture-based image retrieval," *Pattern Analysis and Applications*, vol. 11, no. 2, pp. 141–157, 2008.

[6] M. Calonder, V. Lepetit, C. Strecha, and P. Fua, "Brief: Binary robust independent elementary features," in *Computer Vision–ECCV 2010*, pp. 778–792, Springer, 2010.

[7] A. S. Reis, A. Toren, and M. T. Nicolela, "Clinical optic disc evaluation in glaucoma," *European Ophthalmic Review*, vol. 6, no. 2, pp. 92–97, 2012.

[8] G. D. Joshi, J. Sivaswamy, and S. Krishnadas, "Optic disk and cup segmentation from monocular color retinal images for glaucoma assessment," *Medical Imaging, IEEE Transactions on*, vol. 30, no. 6, pp. 1192–1205, 2011.

[9] M. May, "Automatic Detection of the Optic Disc Within Retinal Images," Master's thesis, University of Manchester, UK, 2008.

[10] D. Morris and C. Donnison, "Identifying the neuroretinal rim boundary using dynamic contours," *Image and Vision Computing*, vol. 17, no. 3, pp. 169–174, 1999.

[11] A. Aquino, M. E. Gegúndez-Arias, and D. Marín, "Detecting the optic disc boundary in digital fundus images using morphological, edge detection, and feature extraction techniques," *Medical Imaging, IEEE Transactions on*, vol. 29, no. 11, pp. 1860–1869, 2010.

[12] R. Abdel-Ghafar and T. Morris, "Progress towards automated detection and characterization of the optic disc in glaucoma and diabetic retinopathy," *Informatics for Health and Social Care*, vol. 32, no. 1, pp. 19–25, 2007.

[13] P. Pallawala, W. Hsu, M. L. Lee, and K.-G. A. Eong, "Automated optic disc localization and contour detection using ellipse fitting and wavelet transform," in *Computer Vision-ECCV 2004*, pp. 139–151, Springer, 2004.

[14] C. Muramatsu, T. Nakagawa, A. Sawada, Y. Hatanaka, T. Hara, T. Yamamoto, and H. Fujita, "Automated segmentation of optic disc region on retinal fundus photographs: Comparison of contour modeling and pixel classification methods," *Computer methods and programs in biomedicine*, vol. 101, no. 1, pp. 23–32, 2011.

[15] P. Tar and N. Thacker, "A quantitative representation for segmentation of martian images," tech. rep., ISBE, Medical School, University of Manchester, 2011.

[16] R. Duda, P. Hart, and D. Stork, *Pattern classification*. pub-WILEY:adr: Wiley, second ed., 2001.