Retinal Fundus Image Constrast Normalization using Mixture of Gaussians

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***Abstract*—We present a fast and robust method to correct contrast variation in retinal fundus imagery. The technique uses a mixture of Gaussians to model the bias of the intensity variation. Typically a two or three component mixture is sufficient to characterize the principal variation due to the spherical geometry of the retina, the high-contrast reflection off the optic nerve and the darker macula. We compare the results with a non-parametric, filtering approach on a standard diabetic retinopathy database of 89 images. Our results indicate that a parametric approach using mixture Gaussian is better at contrast stretching in lesion regions making is an effective pre-processing step for manual and computer aided diagnostic techniques.**

Technical Area(s): F. Biomedical Signal and Image Processing:
1. Medical Image Analysis; 9. Computer Adided Diagnosis

I. Introduction

Digital photographs of the retina are routinely acquired in large screening programmes for the detection and treatment of eye disease to prevent blindness. Diabetic retinopathy is a progressive disease of the eye which is mainly caused by high-level of blood sugar and prevalent in about one third of the diabetic population. The disease causes a variety of lesions on the back of the eye: micro aneurysms; hemorrhage; exudates and neo-vascularization. Because of the large work load for manual grading of these images, a number of computer aided diagnostic systems are being employed to detect early signs of retinopathy and discard the vast majority of images that exhibit no signs of the disease e.g. [1], [2]. Image are acquired using a digital colour camera through a dilated pupil and typically 40-50 degrees of field of view of the retinal can be seen (figure I). All images of this type suffer from non-uniform illumination since the incident light has to be shone in through the pupil as the image is acquired, and the spherical geometry of the eye creates significant inter-reflection and shading artefact. A pre-processing stage is often used to correct the non-uniform illumination before any computer aided algorithm is applied on the pixel data. If applied correctly, this can also aid with the manual inspection of the data. Two common methods are to apply a non-parametric, contrast normalization step to the green channel of the images, or to perform colour histogram matching [3]. The latter is aimed at adjusting the colours to fit better with a learnt colour model for segmentation of hard exudates but does not exclude the normalization of the intensity values.

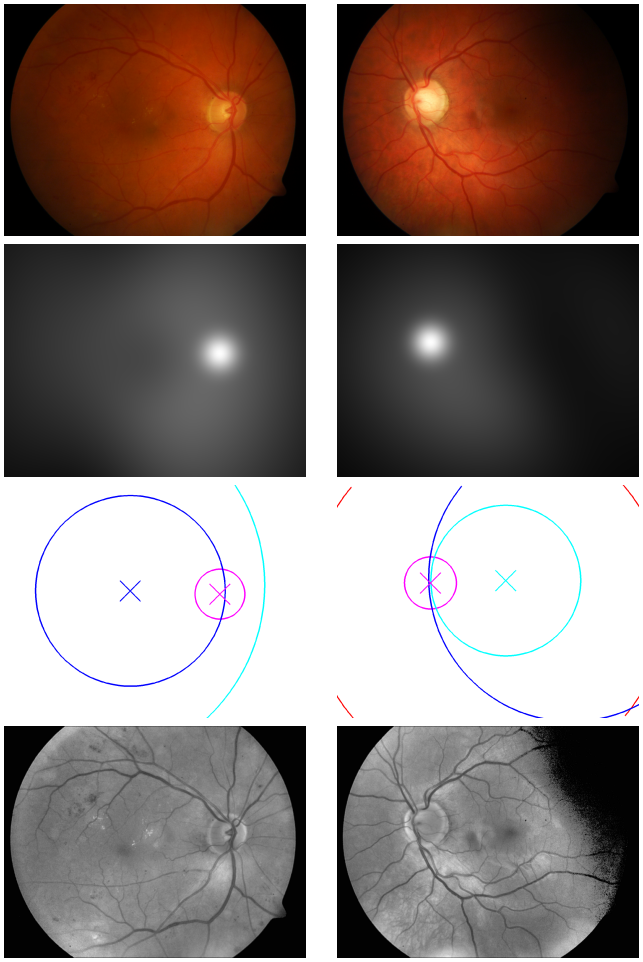

Fig. 1. Illustration results of Mixture of Gaussian fitting and Contrast Normalization with three compoents. Top: Input colour fundus images. Second Row: Estimated bias fields. Third Row: Spatial extents of Gaussian components (optic-disc and macula components centres marked with X). Bottom: constrast normalized.

Here we present a *parametric* approach to contrast normalization that uses a mixture of Gaussians to model the shading artefact or **bias** field. Model based correction of bias in medical imagery has been reported for medical imaging, such as for MRI [4], [5]. After a brief statement of the method, we present comparisons of the effectiveness of the results on a set of 89 images from the DIARETDB1 [6] database using entropy and standard-deviation by considering regions of interest around lesions marked by experts.

II. Method

The biasing model has the form

$$Y(\mathbf{x}) = S_{\times} X(\mathbf{x}) + S_{+}(\mathbf{x}), \tag{1}$$

where the Y is the observed intensity at pixel $\mathbf{x} = (x, y)^T$ and X the unbiased, true pixel intensity. The multiplicative and additive biasing fields are denoted by $S_{\times}$ and S_{+} respectively. For fundus imagery, S_{+} is assumed to be zero, although it can be estimated by other means [5], [7]. The biasing field is further assumed to be low-frequency and the true image to be more or less pice-wise constant. For non-parametric normalization then, $S_{\times}$ can be approximated by low-pass filtering

$$\hat{S}_{\times} = Y * G(\sigma), \tag{2}$$

where $G(\sigma)$ is a suitable low-pass filter with spatial extent σ. Retinal fundus imagery can be of size 2000×1500 or larger and $\sigma = 64$ is required to sufficiently blur the observed image. The normalized image is given by

$$\hat{X} = \frac{Y}{\hat{S}_{\times} + 1}, \qquad \hat{X}' = \frac{\hat{X}}{SD(\hat{X})}. \tag{3}$$

It is not uncommon to stretch the contrast by further dividing by the image standard deviation, SD. Some methods use a rank-filter (median) rather than the local mean (e.g. [2]). For small regions of support, this fares better as it tends to be less influenced by significant features in the vicinity, such as vessels.

The mixture of Gaussians model used here models the bias field as a linear combination of Gaussian functions

$$S_{\times}(\mathbf{x}; \Phi) = \Sigma_k \, a_k \, N_k(\mathbf{x}; \Phi_k), \qquad \Phi = \{a, \mu, \Sigma^{-1}\} \tag{4}$$

where each component is a bi-variate normal Gaussian function, $N(\mathbf{x}; \Phi) = K \exp\{-\frac{1}{2}(\mathbf{x} - \mu)^T \Sigma^{-1} (\mathbf{x} - \mu)\}$ with centroid μ and covariance, Σ^{-1}. The convexity constraint is relaxed, $\Sigma a_k \neq 1$, and the since the model is not a mixture probability density function, the coefficients can be negative and positive: $a \in \mathbb{R}$. By minimizing the residual sum of squares between Y and $\hat{X}(\Phi)$ in the standard way, an estimate of Φ can be obtained:

$$\hat{\Phi} = \min_{\Phi} \left[Y(\mathbf{x}) - S_{\times}(\mathbf{x}; \Phi) \right]^2. \tag{5}$$

III. Experimental Results and Discussion

We compared the low-pass filtering (LP) based technique against the proposed mixture of Gaussians (MoG) normalization on the green channel of a set of 89 colour fundus images from the DIARTETDB1 [6] database. These images are of size 1150×1152 pixels each and all bar 5 contain mild to severe signs of retinopathy. The database also has manually labelled ground-truth data by three experts. Four important disease signs: micro-aneurysms (MA); hard-exudates (HE); soft-exudates (SE) and hemorrhages (HH) have been identified. We looked at 50% confidence regions or interest around HE and HH lesions (figure III) and calculated Shannon entropy in bits and standard deviation; this was compared with entropy before normalization. We used 4 components for the MoG: two for the whole region; one to represent the macula (initialised with a negative amplitude); and one for the optic nerve.

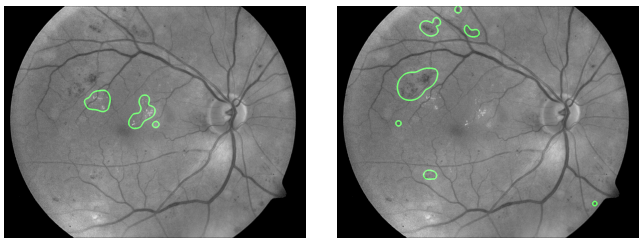

Fig. 2. Confidence regions for lesions: hard-exudate and hemorrhages marked on two examples by experts. Local measures of entropy and standard deviation in these regions of interest were used to compare contrast correction methods.

Under the image and model assumptions, image entropy should drop if the bias field is effectively removed. This is apparent in the results in table III. For both the LP and our MoG method, the contrast is visually better (figure I) and the entropy reduced considerably. Although LP is slightly better than MoG, visual comparisons show that the LP approach fails to deals correctly with the edges of the image since the image convolution (equation 2) is affected by the image boundary. As MoG is implemented by stochastically sampling the foreground image pixels (only 5% were used), the method compares favourably in terms of computation and is unaffected from image boundary artefacts. In all cases, the optic nerve and macula are correctly located by two of the components of the mixture.

Since the aim of any normalization is to detect and quantify lesions, using the ground truth data, we computed entropy and contrast (using standard deviation of the intensity, SD), table III. Across the entire database, only a handful of regions had higher entropy than LP filtering and all had better contrast.

IV. Conclusions

A fast and robust method for model based contrast normalization of retinal fundus imagery has been presented. Normalization of fundus image contrast is an essential preprocessing stage in computer aided diagnostic systems for diabetic retinopathy and other diseases of the eye such as age

Whole Image			
Image	*Entropy*		
	Orig.	LP	MoG
image001	5.06	**3.57**	**3.57**
image002	5.11	**3.38**	3.43
image003	4.31	**3.38**	3.44
image004	6.10	**3.22**	3.47
image005	4.00	**2.94**	3.20

TABLE I
COMPARISON OF LOW-PASS FILTERING BASED CONTRAST NORMALIZATION (LP) AND PROPOSED MIXTURE OF GAUSSIANS APPROACH (MOG) IN TERMS OF THE REDUCTION IN IMAGE ENTROPY IN BITS. SHADING CORRECTION WILL REDUCE THE INFORMATION CONTENT BY MAKING THE HISTOGRAM OF THE IMAGE MORE 'PEAKY'. MOG ENTROPY IS CLOSE TO LP.

Hard Exudate Regions						
Image	*Entropy*			*SD*		
	Orig.	LP	MoG	Orig.	LP	MoG
image001	5.10	3.57	**3.56**	8.27	14.76	**14.73**
image002	7.19	5.53	**5.10**	4.93	10.63	**13.06**
image003	8.10	5.84	**5.26**	5.79	12.36	**14.92**
image004	6.32	**2.94**	3.86	0.20	16.80	**20.01**
image005	4.74	3.80	**3.10**	18.42	12.30	**20.17**

Hemorrhage Regions						
Image	*Entropy*			*SD*		
	Orig.	LP	MoG	Orig.	LP	MoG
image001	9.96	9.41	**8.29**	6.36	8.60	**17.14**
image002	9.05	8.02	**7.84**	5.50	10.16	**14.06**
image003	7.35	4.05	**3.95**	4.21	11.88	**14.20**
image004	9.43	**7.01**	7.25	8.18	13.11	**22.58**
image005	4.62	5.40	**4.22**	16.81	12.51	**16.97**

TABLE II
REGIONAL COMPARISON OF LOW-PASS FILTERING BASED CONTRAST NORMALIZATION (LP) AND PROPOSED MIXTURE OF GAUSSIANS APPROACH (MOG) IN ENTROPY AND STANDARD DEVIATION (SD). FOR THE FIRST FIVE IMAGES OF THE DIARETDB1 DATABASE, MOG IS SUPERIOR IN ALL BUT 1 EXAMPLE. THE LOCAL CONTRAST IS IMPROVED IN ALL CASES BY MOG.

related macular degeneration. The results compare well to non-parametric, filtering based methods. The mixture of Gaussians approach has the advantage of simultaneously being able to locate the optic disc, a common place for false detection, and the macula region which is the critical region for grading disease severity. The method is able to improve the contrast in lesion regions over filtering and is comparable in terms of computational cost.

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