Non-Uniform Illumination Estimation in Fundus Images Using Bounded Surface Fitting

Wannida Sae-Tang 1, Werapon Chiracharit 1, Supaporn Kiattisin 2, and Wuttipong Kumwilaisak 1,

ABSTRACT

Non-uniform illumination estimation in fundus images using bounded surface fitting technique is proposed in this paper. Polynomial surface fitting estimates illuminations of fundus images efficiently even for a non-linear non-uniform illumination estimation. Foreground pixels, i.e., optic disk, fovea, blood vessels, and lesions are excluded in the fitting process for more accuracy. The proposed foreground pixel detection method detects optic disk, fovea, blood vessels, and lesions more accurately for each color band of image, at the same time, yielding lower processing time. The suitable degrees of polynomials in the fitting process have been obtained without fitting iterations. An operation reduction technique is also presented for reducing the processing time and the memory usage. For evaluation, the estimated illuminations are subtracted from the original fundus images. Exudates are subsequently detected using Level-set evolution without re-initialization. Experimental results show that the proposed illumination estimation method is very efficient so that exudates can be detected with high sensitivity and high positive predictive value.

1. INTRODUCTION

Currently, the number of diabetic patients in developed countries is increasing. One reason is that people have the longevity up. The longer a person has diabetes, the more likely they will develop diabetic retinopathy. If left untreated, diabetic retinopathy may cause human vision loss. The early diagnosis and timely treatment can reduce the risk of blindness by 95% [1], so diabetic patients need regular eye screening. Due to the limitation of the number of ophthalmologists, the need of automatic diagnose algorithm of fundus images receives attention from several researchers to off-load works of ophthalmologists. However, fundus image processing suffers from non-uniform illuminations due to image acquisitions, instrumental limitations, and retina responses.

There is some research on contrast enhancement of non-uniform illumination fundus images. Wu et al. [3] enhanced the contrast of the image by using adaptive histogram equalization. It increases the contrast between blood vessels and backgrounds of images in some regions, but it also removes the significant details of images. Xu et al. [4] proposed a better method by using a Laplacian of Gaussian filter after using adaptive histogram equalization. The region with the most change in brightness is subsequently determined. Then, the image is filtered again by a median filter. This method has a better performance in terms of contrast enhancement than the method proposed in [3]. However, it removes the important foreground information such as optic disk, fovea, and lesions as well.

There is research on non-uniform illumination correction in fundus images. Yang et al. [5] corrected the illumination of fundus images by dividing the image by its over-smooth version. The over-smooth version is obtained by using a large median filter. This method is very simple, but the result was not good enough. Foracchia et al. [6] and Grisan et al. [7] modeled fundus images as having foreground-background. The background is assumed as having the multiplicative noises and the additive noises. Both noises are estimated in the intensity band of image in HSV color space for later background correction. If the assumption is fault, the result could not be accurate.

In addition, there is research on non-uniform illumination estimation in fundus images. Lin and Zheng [8] proposed background subtraction of retinal blood vessels. Fundus image is modeled as having two components, i.e., blood vessels (foreground) and background. The background is estimated by averaging the neighborhood intensity and using threshold averaging. The result is suitable for later vessels segmentation. However, the method cannot be applied for optic disk, fovea, and lesion detection. Lu and Lim [9] estimated background of fundus images by using polynomial curve fitting on each column and row of the intensity band of image in HSV color space. Therefore, there is no relationship between row and column in the fitting. Moreover, the iteration is needed for both row and column fittings. In each iteration, pixels with the maximum fitting error are removed if the error is larger than a pre-defined threshold. If the threshold is not set properly, the background cannot be estimated accurately. Narasimha-

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Iyer et al. [10], [11] estimated illumination of fundus images by using polynomial surface fitting. The result is better than that of other methods mentioned above. Surface fitting is efficient even for a non-linear non-uniform illumination estimation. There are the relationships between rows and columns of images. In addition, it can select pixels used in the fitting process. Optic disk, fovea, blood vessels, and lesions are defined as the unwanted pixels in the illumination estimation. The accurate detection of these unwanted pixels allows us to obtain the more accurate estimated illumination. However, the unwanted pixels are extracted separately and complexly in [10], [11] causing the numerous processing time. Blood vessels were detected using the tracing algorithm developed by Fritzse et al. [12]. Optic disk was detected using the algorithm built on the algorithm of Hoover et al. [13]. Fovea was detected using the modified version of the method described by et al. [14]. Optic disk and fovea are modeled as circles, although they may not appear as circles or may not exist in fundus images. Moreover, lesions are detected roughly with 10th percentile of intensity of the image that may not be correct in some cases. In addition, the optic disk, fovea, blood vessels, and lesions should be detected separately for each color band of the image. Inaccurate optic disk, fovea, blood vessel, and lesion detections cause the inaccurate illumination estimation. Another disadvantage of the methods proposed in [10], [11] is the need of fitting iterations.

The rest of this paper is organized as follows. Section 2 describes in details of the proposed illumination estimation methods. Section 3 describes parameters in the proposed method. Section 4 gives the experimental results to evaluate the proposed illumination estimation method. Finally, Section 5 concludes this paper.

2. PROPOSED METHOD

Figure 1 illustrates the proposed non-uniform illumination estimation in color fundus images. Illumination is estimated from R, G, and B components independently. This is more suitable than the use of only green band of image or only intensity band of image in HSV color space, because the significant details of retinal structures and lesions may be on any color band of images.

2.1 Upper/lower bound calculations

Upper bound and lower bound are firstly calculated for the later unwanted pixel detection. Three single band images are smoothed by low pass filtering as described by equation (1).

\[
I_L(x, y) = \sum_{i=-k}^{k} \sum_{j=-k}^{k} I(x+i, y+j) \cdot h(i, j),
\]

where \(I(x, y)\) and \(I_L(x, y)\) denote the single band image and the low frequency image, respectively. \(h(i, j)\) denotes the filter mask. In this paper, the average filter is used. After obtain the low frequency image, the high frequency image can be easily obtained as

\[
I_H(x, y) = |I(x, y) - I_L(x, y)|,
\]

where \(I_H(x, y)\) is the high frequency image. The upper bound is then calculated by adding the low frequency image \(I_L(x, y)\) by the standard deviation of the high frequency image \(I_H(x, y)\) as described by equation (3).

\[
UB(x, y) = I_L(x, y) + \sqrt{\frac{1}{N} \sum_{(x,y)} (I_H(x, y) - I_H)^2},
\]

where \(UB(x, y)\) denotes the upper bound at pixel \((x, y)\). N denotes the number of pixels in the image.
$\overline{I}_H$ denotes the statistic mean of $I_H(x, y)$. In the same way, the lower bound is calculated by subtracting the low frequency image by the standard deviation of the high frequency image as described by equation (4).

$$LB(x, y) = I_L(x, y) - \sqrt{\frac{1}{N} \sum_{(x,y)} (I_H(x, y) - \overline{I}_H)^2},$$

where $LB(x, y)$ denotes the lower bound.

2.2 Unwanted pixel detection

Optic disk, fovea, blood vessels, and lesions are defined as the unwanted pixels in illumination estimation, and they are defined as the foreground of image. They are detected by using upper/lower bounds. The pixels that represent the intensity higher than the upper bound or lower than the lower bound are defined as the unwanted pixels and are set to zero as described by equation (5).

$$w(x, y) = \begin{cases} 0, & UB(x, y) < I(x, y) \\ 0, & I(x, y) < LB(x, y) \\ 1, & LB(x, y) \leq I(x, y) \leq UB(x, y) \end{cases},$$

where $w(x, y)$ is the weighting function of pixel $(x, y)$. Figure 2 compares the unwanted pixel detection results between the proposed method and the method used in IRHSF [10]. The unwanted pixels which correspond to zero are shown with black pixels. The different color band, the different appearances of optic disk, fovea, blood vessels, and lesions become. This is the reason why the separable color band detection is needed. Optic disk and fovea are detected as circles by the method used in IRHSF while the proposed method detects them as the shapes they appear on each color band. False positives in unwanted pixel detection occurred in IRHSF reduce the data points used in the fitting process. It seems not important because the surface fitting technique is very robust even some data points are lost. However, our proposed method detects blood vessels and lesions with higher sensitivity. This is important because all detected pixels are removed in the fitting process. False negatives in unwanted pixel detection occurred in IRHSF significantly degrade the accuracy of illumination estimation. Moreover, our proposed method detects optic disk, fovea, blood vessels, and lesions in one shot for each color band so that the processing time is reduced. For images with $390 \times 512$ pixels in size, the averaging processing time per image is reduced from 15.353 to 2.265 seconds.

2.3 Weighted surface fitting

After detecting unwanted pixels, the illumination of image can be estimated by equation (6).

$$\overrightarrow{E} = S \overrightarrow{P},$$

where $\overrightarrow{E}$ is the estimated background vector, $S$ is the surface matrix, and $\overrightarrow{P}$ is the parametric surface vector. The best surface for fundus image fitting seems to be a polynomial surface, because the nature of illumination of fundus images is smooth. Hence, the surface matrix is assigned to be $A^k$ order polynomial which includes $M$ terms or $M$ parameters. The parametric surface fitting equation can be formulated by equation (7).

$$\begin{pmatrix} E(1,1) \\ \vdots \\ E(x, y) \\ E(m,n) \end{pmatrix} = \begin{pmatrix} 1 & 1 & \cdots & 1 & 1 \\ \vdots & \vdots & \cdots & \vdots & \vdots \\ x^A & x^{A-1}y & \cdots & y & 1 \\ \vdots & \vdots & \cdots & \vdots & \vdots \\ m^A & m^{A-1}n & \cdots & n & 1 \end{pmatrix} \begin{pmatrix} P_1 \\ \vdots \\ P_M \end{pmatrix},$$

where the image size is $m \times n$ pixels, and $(x, y)$ is the pixel coordinate. The parametric surface vector can be calculated by equation (8).

$$\overrightarrow{P} = (S^TWS)^{-1}(S^TW) \overrightarrow{T},$$

where $\overrightarrow{T}$ is the intensity vector of the original image and $W$ is the diagonal weight matrix defined as

$$W = \begin{pmatrix} w(1,1) & 0 & \cdots & 0 \\ 0 & \ddots & \cdots & 0 \\ 0 & \cdots & 0 & w(m, n) \end{pmatrix}.$$
Fig. 2: Result of unwanted pixel detection; (a) original fundus image (b) IRSHF (c) red band of the proposed method (d) green band of the proposed method (e) blue band of the proposed method.

Fig. 3: Result of illumination estimation; (a) RGB (b) red band (c) green band (d) blue band.

Fig. 4: Unwanted pixel detection results with various filter mask sizes; (a)-(c) 5 x 5 pixels (d)-(f) 10 x 10 pixels (g)-(i) 20 x 20 pixels (j)-(l) 40 x 40 pixels.

3.2 Degree of polynomial

The question is that what degree of polynomial should be used in the surface fitting. The way to obtain the suitable degree of polynomial is to consider the variance of the residual [15]. The residual of the surface fitting is the difference between the input image and the surface fitted image. The variance of the
residual can be calculated by equation (10).

\[ \sigma^2 = \frac{\sum_{(x,y)} e(x,y)^2}{N - A - 1}, \]  

where \( e(x,y) \) is the residual at pixel \((x,y)\). The degree which significantly reduces the variance of the residual is selected. To give an example, variances of residuals are calculated and shown in Table 1, where the subscript numbers denote the degrees of polynomials. The fourth-degree of polynomial is selected for the red band and the green band, because the variance of the residual is significantly reduced when the degree of polynomial increases from 3 to 4. In the same way, the fifth-degree of polynomial is selected for the blue band. However, the processing time is very large if the size of image is too large. Hence, the image size is reduced by using a pixel sampling technique in order to find the suitable degree of polynomial. In this case, the factor used in the image sampling is 5, so the image with 390 \times 512 pixels in size is reduced to 78 \times 102 pixels. Variances of residuals in the sampled image are shown in Table 2. We can see that the results of degree selections are the same as the results of degree selections with the non-sampled image, while the processing time is reduced from several hours to only four seconds per image.

4. EXPERIMENTAL RESULTS AND DISCUSSIONS

4.1 Materials and program

Materials used in the experiments are six 24-bit color fundus images with 565 \times 584 pixels in size from DRIVE databases [16], eight 32-bit color fundus images from REVIEW databases [17], and eighty nine 24-bit color fundus images with 1500 \times 1152 pixels in size from DIARETDB1 database [18]. They are tested on MATLAB 7.7.0 (R2008b) with Intel Core\textsuperscript{Tm}2 Duo CPU E7500 @ 2.93 GHz.

4.2 Illumination estimation results and discussions

The proposed illumination estimation method is compared with other three illumination estimation methods, i.e., Low pass filtering, Surface fitting without data weighting, and IRHSF [10], [11]. Materials used in this evaluation part are fourteen images from DRIVE and REVIEW databases [16], [17]. Figure 5 compares the estimated illuminations resulted by several methods. The results show that Low pass filtering cannot estimate illuminations of fundus images effectively. Optic disk, fovea, blood vessels, and lesions are found in the estimated illumination. Surface fitting without data weighting faults in estimating illumination for most foreground pixels. IRHSF faults in estimating illumination for some foreground pixels due to some wrong weighted pixels while the proposed method can solve these problems.

4.3 Exudate detection results and discussions

The estimated illuminations resulted by several methods, i.e., Low pass filtering, Surface fitting without data weighting, and IRHSF are subtracted from the original image to obtain the foregrounds of images. The negative values from the background subtraction are bounded by zero, so over-dark portions, i.e., fovea, blood vessels, and dark lesions are suppressed. Therefore, the foreground of image includes only optic disk and exudates. Optic disk is then re-
moved from the image by setting the region of interested. Finally, exudates are detected for quantity evaluation using Level-set evolution without re-initialization proposed by Li et al [19]. Fourteen images that contain exudates from DRIVE and REVIEW databases are used. The results of exudate detection are justified by two experts. Sensitivity, specificity, positive predictive value (PPV), accuracy, and misclassified proportion (MP) are calculated to evaluate the results of exudate detection by the following equations.

\[
\text{Sensitivity} = \frac{TP}{TP + FN} \quad (11)
\]

\[
\text{Specificity} = \frac{TN}{TN + FP} \quad (12)
\]

\[
\text{PPV} = \frac{TP}{TP + FP} \quad (13)
\]

\[
\text{Accuracy} = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (14)
\]

\[
\text{MP} = \frac{FP}{(TP + TN + FP + FN)} \quad (15)
\]

Where true positive (TP) is the number of exudate pixels correctly detected, true negative (TN) is the number of non-exudate pixels correctly identified as non-exudate pixels, false positive (FP) is the number of non-exudate pixels wrongly detected as exudate pixels, and false negative (FN) is the number of exudate pixels that cannot be detected. Sensitivity is the probability that the proposed method can classify the pixels of exudates as exudates. Specificity is the probability that the proposed method can classify the pixels of non-exudates as non-exudates. PPV is the probability that the pixels classified as exudates are really exudates. Specificity and accuracy are not very meaningful because the true negative value is always very high. Specificity and accuracy are always close to 100% regardless of exudate detection method.

Figure 6 compares exudate detection results when illuminations are estimated by several methods. Table 3 shows average sensitivity, average specificity, average PPV, average accuracy, and average MP. All surface fitting methods achieve comparably high PPV in detecting exudates. It shows that Surface fitting is very robust even some data points are lost. In case of IRHSF, some data points are lost in the fitting process because of FP in detecting unwanted pixels. Surface fitting can estimate those lost data, and it results in the low number of FP or high PPV in detecting exudates. In case of surface fitting without data weighting, every pixel is used, so the PPV is slightly higher than that of IRHSF. Low pass filtering is a very simple method which achieves high PPV in detecting exudates as well. Anyway, it could not be effective if the filter mask size is not chosen properly.

Although all methods achieve high PPV in detecting exudates, the proposed method achieves the highest sensitivity in detecting exudates. Many exudates are found in the estimated illumination in case of Low pass filtering, so they are lost from the foreground of images causing very low sensitivity in detecting exudates. In case of surface fitting without data weighting, all pixels are used in the fitting process which results in inaccurate illumination estimation and low sensitive exudate detection. This is because the surface fitting is not very robust to FN in detecting unwanted pixels. That is the reason why we need to obtain the accurate unwanted pixels for surface fitting. IRHSF achieved 84.31% sensitivity in detecting exudates that is higher than that of surface fitting.

![Figure 6](image)

**Fig.6:** Exudate detection results; (a) ground truth (b) Low pass filtering (c) Surface fitting without data weighting (d) IRHSF (e) proposed method.

**Table 3:** Comparison of exudate detection methods in fourteen images that contain hard exudates (DRIVE and REVIEW databases).

<table>
<thead>
<tr>
<th>Method</th>
<th>Average sensitivity (%)</th>
<th>Average specificity (%)</th>
<th>Average PPV (%)</th>
<th>Average accuracy (%)</th>
<th>Average MP (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low pass filtering</td>
<td>54.98</td>
<td>99.93</td>
<td>92.15</td>
<td>99.29</td>
<td>0.06</td>
</tr>
<tr>
<td>Low pass filtering without data weighting</td>
<td>67.53</td>
<td>99.92</td>
<td>92.69</td>
<td>99.57</td>
<td>0.07</td>
</tr>
<tr>
<td>IRHSF [10, 11]</td>
<td>84.31</td>
<td>99.90</td>
<td>92.25</td>
<td>99.75</td>
<td>0.09</td>
</tr>
<tr>
<td>Proposed method</td>
<td>91.84</td>
<td>99.90</td>
<td>92.81</td>
<td>99.79</td>
<td>0.09</td>
</tr>
</tbody>
</table>
Table 4: Comparison of exudate detection methods in forty seven images that contain hard exudates (DIARETDB1 database).

<table>
<thead>
<tr>
<th>Method</th>
<th>Average sensitivity (%)</th>
<th>Average specificity (%)</th>
<th>Average PPV (%)</th>
<th>Average MP (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soparak et al. [20], [21]</td>
<td>43.48</td>
<td>99.31</td>
<td>25.48</td>
<td>0.68</td>
</tr>
<tr>
<td>Ravishankar et al. [22]</td>
<td>58.21</td>
<td>98.09</td>
<td>13.37</td>
<td>1.90</td>
</tr>
<tr>
<td>Walter et al. [23]</td>
<td>66.00</td>
<td>98.64</td>
<td>19.45</td>
<td>1.34</td>
</tr>
<tr>
<td>Weller et al. [24]</td>
<td>70.48</td>
<td>98.84</td>
<td>21.32</td>
<td>1.10</td>
</tr>
<tr>
<td>Kande et al. [25]</td>
<td>80.00</td>
<td>98.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proposed method</td>
<td>89.48</td>
<td>99.08</td>
<td>80.74</td>
<td>0.81</td>
</tr>
</tbody>
</table>

Table 5: Comparison of exudate detection methods in forty two images that do not contain hard exudates (DIARETDB1 database).

<table>
<thead>
<tr>
<th>Method</th>
<th>Average specificity (%)</th>
<th>Average MP (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soparak et al. [20], [21]</td>
<td>99.28</td>
<td>0.71</td>
</tr>
<tr>
<td>Ravishankar et al. [22]</td>
<td>97.53</td>
<td>2.47</td>
</tr>
<tr>
<td>Walter et al. [23]</td>
<td>99.22</td>
<td>0.77</td>
</tr>
<tr>
<td>Weller et al. [24]</td>
<td>98.74</td>
<td>1.20</td>
</tr>
<tr>
<td>Kande et al. [25]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proposed method</td>
<td>99.48</td>
<td>0.92</td>
</tr>
</tbody>
</table>

Without data weighting. However, there are several false negatives in detecting blood vessels and lesions by IRHSF, and they degrade the sensitivity of the exudate detection. The proposed method achieved 91.84% sensitivity in detecting exudates because of the more accurate unwanted pixel detection.

The proposed method is also compared with other five exudates detection methods because the exudates detection method is fixed in the previous experiment, i.e., Level-set evolution without re-initialization. Eighty nine retinal images from DIARETDB1 database [17] are used in this experimental part.

Forty seven images contain exudates, but the rest images do not. They include manually labeled images that we use as the ground truth in our experiment. The proposed method is compared with the methods proposed by Soparak et al. [20], [21], Ravishankar et al. [22], Walter et al. [23], Weller et al. [24], and Kande et al. [25]. All compared methods are based on mathematical morphology and were validated using DIARETDB1 database. Weller et al. [24] used the contrast enhancement method proposed by Soille et al. [26] before detecting exudates. That method improves the sensitivity of exudate detection, but it also increases FP causing the low PPV. Kande et al. [25] used the local contrast enhancement method proposed by Sinthanayothin et al. [27]. The method increases the contrast of images, but it introduces noises to the images. The exudate detection results are shown in Table 4 and Table 5.

For images with hard exudates, the proposed method achieves higher average PPV than that of other methods. For images without hard exudates, the proposed method achieves the highest average specificity and the lowest average MP. It shows that the proposed method significantly reduces FP in detecting exudates and simultaneously keeps high sensitivity in detecting exudates. This is because of the effective illumination estimation.

5. CONCLUSION

Non-uniform illumination which is especially a problem in fundus image processing is estimated by using bounded weighted surface fitting technique. The advantage of the surface fitting is that one can select the data used in the fitting process. Also, polynomial surface fitting is efficient even for a non-linear non-uniform illumination estimation. The unwanted pixels in illumination estimation, i.e., three key retinal structures and lesions which are the foreground of images are detected fast and accurately using upper-lower bounds instead of performing feature extractions. The operation reduction is also proposed in order to reduce the processing time and the memory usage. Experimental results show that the proposed illumination estimation method is very efficient so that exudates can be detected with high sensitivity and high PPV. Although this paper focuses on retinal images, the proposed illumination estimation method may be applied to other digital images whose illuminations are non-linear non-uniform.

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References


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