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Localization of Optic Disk Using Independent Component Analysis and Modified Structural Similarity Measure

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Abstract

Localization and segmentation of Optic Disk (OD) is an important prerequisite for automatic detection of Diabetic Retinopathy (DR) from digital retinal fundus images. Considerable research has been done to isolate OD with varying degrees of success but on a limited number of images. In this paper we propose a novel algorithm based on Independent Component Analysis (ICA) coupled with a modified Structural Similarity Index Measure (m-SSIM) for localization of OD. We have tested our method on 100 normal retinal images (achieving 100 % success) and 232 diseased retinal images (achieving 75% success), thereby demonstrating a significant improvement over two other existing methods.

1 Introduction

The brightest feature of a healthy digital retinal fundus image is the OD. It is approximately circular and measures around 1800 µm. Retinal vasculature originates from OD. Since the OD has characteristics similar to exudates, it is vulnerable to be detected as a false positive. Hence locating and segmenting OD accurately is an important task in automated detection of lesions of DR. Further OD localization helps to determine the location of macula and fovea. In the literature we find that the OD is localized based on the following properties: (a) It is the largest region that consists of pixels with the highest gray levels. (b) It is the area with highest variation of intensity of adjacent pixels. (c) It is the convergence point of the blood vessels.

Techniques in [1] and [2] exploit the first property, while [3] relies on the second one. These methods demonstrate good results in normal retinal images where OD is the brightest. But in the presence of bright lesions similar to OD in the image, they result in incorrect OD localization. Methods in [4], [5] and [6] exploit the third property. In these methods the segmented blood vessels are tracked to the point of their convergence. Foracchia et al. [7] builds a geometrical model of blood vessels and localizes the OD by simulated annealing. All these methods require preliminary segmentation of blood vessels, which by itself is a complicated task and the final results are dependent on the accuracy with which the blood vessels are segmented.

In this paper, we propose a novel approach of OD localization based on the similarity of the projection of candidate regions to the ICA basis space respectively. In [11] it has been quoted that ICA performs significantly better using cosines as similarity measure than Euclidean distance. In this paper we have recommended a modified structural similarity measure (m-SSIM) and have illustrated that it outperforms cosines measure. Further we have demonstrated that (i) our method is robust when compared to the method prescribed in [6] and (ii) our method performs significantly better than the PCA based method in [8].

2 Preliminaries

We briefly introduce ICA and SSIM here.

2.1 ICA

ICA finds structure in the multivariate data by exploiting the higher order statistics. ICA has been successfully applied to face recognition problem [11]. The goal of ICA is to linearly transform the data so that the transformed variables are as statistically independent as possible. ICA defines a generative model for the observed multivariate data, which is typically given as a large database of samples. In the model, the data variables are assumed to be linear mixtures of some unknown latent variables, and the mixing system is also unknown. The latent variables are assumed to be non-Gaussian and mutually independent and are known as independent components of the observed data. These independent components can be obtained by ICA.

The ICA method can be briefly formulated as follows: let **S** be the vector of unknown source signals and **X** be vector of observed mixtures. If **A** is an unknown mixing matrix, then the mixing model can be written as **X = AS**. The task is to estimate the independent source signals **U** by computing the separating matrix **W** that corresponds to the mixing matrix **A** using the following relation

$$\mathbf{U = WX = WAS}$$

First, the observed samples are whitened. Whitening means that the observed variable **x** is linearly transformed to a variable $\mathbf{v=Qx}$ such that $\mathbf{E[vv^T]=I}$. This transformation is always possible and indeed it can be accomplished by PCA. Let us denote the whitened samples by **Z**. Then, we search for the matrix such that the linear projection of

the whitened samples by the matrix **W** has maximum non-Gaussianity of data distribution. The kurtosis of $\mathbf{U_i} = \mathbf{W_i}^T\mathbf{Z}$ is computed and the separating vector $\mathbf{W_i}$ is obtained by maximizing the kurtosis.

$$\mathbf{kurt(U_i) = |E\{(U_i)^4\} - 3(E\{(U_i)^2\})^2|}$$

Alternatively one could use a normalized variation of differential entropy called negentropy to measure non-Gaussianity. For an excellent treatise on ICA, readers are referred to [10]. We have used the FastICA algorithm [12] developed by Hyvarinen et al [10].

2.2 SSIM

Unlike Minkowski error metric that is based on point-wise signal differences, the SSIM proposed in [9] captures the structural information in the image to provide a good approximation to perceived image distortion. The structural information are those attributes that represent the structure of objects in the image, independent of luminance and contrast. Structure comparison between two images is conducted after luminance subtraction and variance normalization. Specifically, we associate the two normalized images $(\mathbf{x}-\mu_\mathbf{x})/\sigma_\mathbf{x}$ and $(\mathbf{y}-\mu_\mathbf{y})/\sigma_\mathbf{y}$ with the structure of the two input images **x** and **y**, where μ_x and μ_y are the luminance of the images x and **y** respectively and σ_x and σ_y are the contrasts of **x** and **y** respectively. The correlation between these is a simple and effective measure to quantify the structural similarity. Thus, we define the structure comparison function as

$$\mathbf{st}(\mathbf{x},\mathbf{y}) = \frac{\mathbf{i}+\sigma_{\mathbf{xy}}}{\mathbf{i}+\sigma_\mathbf{y}\sigma_\mathbf{x}}$$

where σ_{xy} is the covariance between **x** and **y** and i is a constant used to avoid the instability when $\sigma_y\sigma_x = 0$. The SSIM is defined as $\mathbf{s}(\mathbf{x},\mathbf{y})=[\mathrm{l}(\mathbf{x},\mathbf{y})]^a.\ [\mathrm{c}(\mathbf{x},\mathbf{y})]^b.\ [\mathrm{st}(\mathbf{x},\mathbf{y})]^c$ where $\mathrm{l}(\mathbf{x},\mathbf{y})$ is the luminance comparison function given by

$$\mathrm{l}(\mathbf{x},\mathbf{y}) = \frac{2\mu_\mathbf{x}\mu_\mathbf{y}+\mathbf{j}}{\mu_\mathbf{x}^2+\mu_\mathbf{y}^2+\mathbf{j}}$$

, the constant j being used to avoid the instability when $\mu_x\mu_x + \mu_y\mu_y = 0$.

$\mathrm{c}(\mathbf{x},\mathbf{y})$ is the contrast comparison function given by

$$\mathrm{c}(\mathbf{x},\mathbf{y}) = \frac{2\sigma_\mathbf{x}\sigma_\mathbf{y}+\mathbf{k}}{\sigma_\mathbf{x}^2+\sigma_\mathbf{y}^2+\mathbf{k}}$$

, the constant k being used to avoid the instability when $\sigma_x.\sigma_x + \sigma_y\sigma_y = 0$.

a,b,c are positive constants used to adjust the relative importance of the luminance, contrast and structure components respectively. The values of i, j, k and a, b,c are chosen as described in [9].

3 Proposed Method in Detail

3.1 Step 1: Generating Basis Images for OD and non-OD regions

Since the diameter of optic disc is in the range of 70-105 pixels in the retinal image of 640x480 pixels, manually cropped optic discs of size 110x110 were taken as the training images for the ICA algorithm.

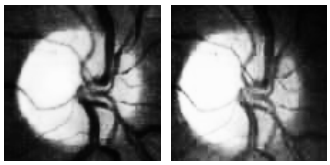

Figure 1. Two contrast enhanced OD templates from the set of training OD templates that is input to the ICA algorithm

Due to the degradation in quality of contrast as we move from the centre towards the boundary of fundus image where the OD is present, the contrast of the training images is enhanced using the sigmoid function to clearly distinguish vessel convergence from OD background. Two examples in gray scale version are shown in Fig 1. Each training image is treated as a column vector of 12100x1 dimensions and appended to form a single matrix of 12100xN where N is the number of the training images. This matrix is then processed using the FastICA algorithm [12] corresponding to architecture I [11] (which considers the input optic disc images as a linear combination of statistically independent basis images, combined by an unknown matrix) to obtain the ICA optic disc basis images . A sample of basis images is shown in Fig 2. Similarly we also obtain the non-OD basis images based on images taken from non-OD regions sample.

3.2 Step 2: Identifying a set of candidate regions in Test Image

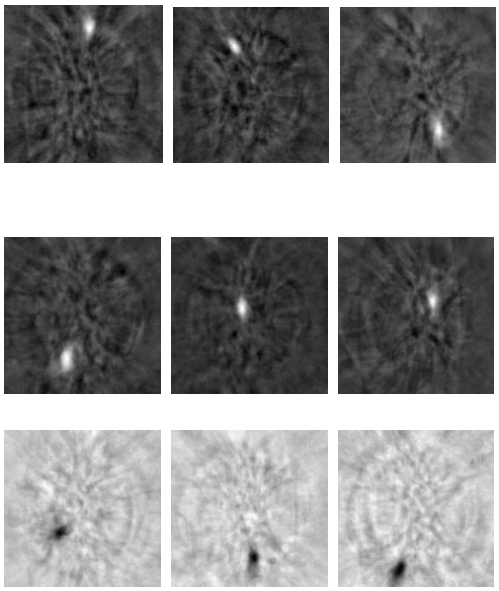

Figure 2. A sample of OD basis images output by ICA algorithm when the set of training OD templates was given as input.

By transforming the input RGB image to YIQ and HSV space we obtain Y and H components. Pixels with the highest 5% intensity level (Y) are selected along with those pixels having the hue (H) in the yellow range. A clustering mechanism is then used to group these pixels into clusters, in which a pixel which qualifies as per the intensity and yellow hue criterion is assigned to a cluster depending on whether it is adjacent to any of the pixels belonging to that cluster. After all the pixels are assigned that way, a threshold is imposed to abandon a cluster in which the pixel count falls below the threshold limit (< 200). The clusters which remain after this step qualify as the candidate regions for further processing. As the diameter of optic disc is in the range of 70-105 pixels in the retinal image of 640x480 pixels, each candidate region is defined as a square of 110x110 pixels with the centroid of the cluster as the center. We denote the set of candidate regions as C1.

3.3 Step 3: Computing m-SSIM

We have proposed a modified structural similarity index measure (m-SSIM) which is a weighted measure. The basic SSIM values are weighted by the factors derived from the dot products of the test image with basis images.

Definition: Let the set of ICA based basis images derived from the set of training images described earlier be denoted by $\mathbf{B}=\{\mathbf{B_1},\ldots, \mathbf{B_q}\}$. Let the set of candidate regions obtained from the test image be denoted by $\mathbf{A}=\{\mathbf{A_1},\ldots, \mathbf{A_r}\}$. The structural similarity vector $\mathbf{SS(A_i,B)}$ of dimension 1x q is given by $[\mathbf{s(A_i,B_1)}\ \mathbf{s(A_i,B_2)}\ \ldots\ \mathbf{s(A_i,B_q)}]$ where $\mathbf{s(A_i, B_j)}$ is computed using basic SSIM. Then

$$\mathbf{m\text{-}SSIM(A_i, B)} = \sqrt{\sum_{j=1}^{q} \left[(A_i^T B_j) \times s(A_i, B_j)\right]^2}$$

3.4 Application of m-SSIM

Among the candidates which have their similarity norm value with respect to the optic disc basis greater than their similarity norm value with respect to the non-optic disc basis, the candidate region having the maximum similarity norm value with respect to the optic disc basis is chosen as the optic disc region.

4 Justification for modifying SSIM

Here we elucidate the reasons to amend the basic SSIM proposed in [9]. The similarity that exists between the basis images is determined by computing the matrix of similarities between the basis images (using basic SSIM), a 5 x 5 submatrix (call it as M) of which is shown in Table 1.

Though M showed maximum value i.e. 1 all along the diagonal, it showed non-zero values elsewhere and some values significant enough i.e. values to the order of 0.4 on a scale of 0-1, to suggest considerable structural similarity between some of the basis images. This similarity existing between basis images, which by theory are independent, may affect the recognition performance of the proposed method. To overcome this, we performed an iterative application of ICA and determined the matrix M of similarities between basis images, but of no avail. Hence there is a need to make the similarity measure more discriminatory i.e. to search for ways of getting the ideal M which peaks along the diagonal while having all off-diagonal elements as zeros (or at least a negligible value close enough to zero). Towards this end we performed the following experiments:

Experiment 1. In this experiment we want to determine whether any non-OD region has significant similarity to OD basis images. We considered two non-OD regions viz a natural image patch (NP) and an exudate patch (EP). The similarity of NP and EP to OD basis images is computed and tabulated. A sample of this table is shown in Table 2.

Table 1. Similarity between basis images B1 – B5

	B1	B2	B3	B4	B5
B1	1.000	0.313	0.448	0.401	0.422
B2	0.313	1.000	0.383	0.332	0.375
B3	0.448	0.383	1.000	0.372	0.397
B4	0.401	0.332	0.372	1.000	0.341
B5	0.422	0.375	0.397	0.341	1.000

As is evident, the similarity measure shows low values throughout in both the cases. This indicates that the structural similarity approach is effective in rejecting the non-optic disc regions by allotting low values.

Experiment 2: In this experiment we want to test the inter-class discriminatory power of SSIM against the intra-class discrimination. A set of mixture images is generated

Table 2. Similarity of NP and EP to basis images B1-B5

	B1	B2	B3	B4	B5
NP	.12	.15	.13	.30	.27
EP	.23	.17	.20	.17	.17

by combining basis images B1, B2, B3 in a certain ratio, and the similarity of these mixtures to the OD basis images B1, B2, B3, B4 and B5 is computed and shown in Table 3.

In Table 3 M1, M2 and M3 are mixed as:

Mixture M1 – Optic Disc basis images B1, B2 and B3 are mixed in the ratio of 50:40:10

Mixture M2 – Optic Disc basis images B1, B2 and B3 are mixed in the ratio of 20:60:20

Mixture M3 – Optic Disc basis images B1, B2 and B3 are mixed in the ratio of 20:30:50

The similarity matrix in Table 3 faithfully shows peaks in similarity with the corresponding basis images more or

less proportionate to the mixing ratios, for eg., upon mixing basis images B1, B2, B3 in the proportion of 0.2:0.6:0.2, we find that the peak similarity is with respect to the basis image B2 but annoyingly the similarity values with respect to basis images B1 and B3 are not convincingly large enough compared to similarity values with other basis images like B4 and B5 for a clear cut demarcation or discrimination based on similarity values alone. That is, the similarity measure provides good discrimination when it comes to separation of optic disc and non-optic disc classes (i.e. good inter-class discrimination) but poor discrimination when it comes to images within a class (i.e. poor intra-class discrimination).

Table 3. Similarity of 3 mixtures M1, M2, and M3 to basis images B1-B5

	B1	B2	B3	B4	B5
M1	.69	.67	.41	.41	.39
M2	.43	.88	.41	.39	.44
M3	.38	.59	.62	.39	.37

For the same mixtures tabulated in Table 3, the similarity matrix weighted with dot products is computed and is shown in Table 4. Upon retaining only those elements of weighted similarity matrix which are above a set threshold (say 10^{-3}), it is clear that matrix of similarities M now has the desirable properties close to the ideal. Hence we proposed m-SSIM as a weighted measure, weighted by the factors derived from the dot products of the test image with basis images.

5 Experimental Set Up, Results and Discussions

We implemented the proposed approach in MATLAB (version 7) on a P4 machine (3.00 GHz). Our database included 300 diseased images and 150 normal images of resolution 640 X 480. We selected 82 OD and non-OD templates of size 110 x 110 for training. The H and Y range for identifying candidate regions was chosen from the interval [0.1 0.15] and [0.75 1] respectively. The threshold limit for cluster count was set to 200.

We tested our method on 100 normal retinal images, achieving 100% success and on 232 diseased retinal images, achieving 74% success. The PCA based approach proposed in [8] performs equal to ICA on normal images but the success percentage is only 60 on diseased retinal images. In [6] the OD is determined as the intersection of set of brightest pixels and set of pixels in the neighborhood of convergence of blood vessels. Here the brightest candidate regions are located by undoing the effect of vignetting. This procedure reports 80% success on diseased retinal images but is highly sensitive to a threshold value that is stabilized by illumination equalization to yield pixels inside the optic nerve [6]. Inspite of this preprocessing of illumination equalization, a small change in this threshold drastically reduces the success percentage under 20 whereas our method is more robust and performs uniformly well with same H and Y value, reporting 74% success. Also we compared the standard cosines measure with our m-SSIM. We found that on diseased retinal images from our database, cosines measure reported only 65% success. A sample of OD localization results are presented in Fig 3 where the black square localizes OD and the red squares are other candidate regions. Fig 3(a) is a result on a normal retinal image. Please note that in Fig 3(b), there are many exudates similar to OD but our algorithm localized OD correctly. PCA based method failed in this case (see Fig 3(c)). Also ICA based on cosines measures failed to localize OD correctly in this case(see Fig 3(d)).

Table 4. Similarity of mixtures to basis images based on m-SSIM

	B1	B2	B3	B4	B5
M1	1	0.6668	0	0	0
M2	0.6668	1	0	0	0
M3	0	0.4288	1	0	0

Presence of illumination imbalance could pose problems for OD localization. For e.g. our method failed to localize OD correctly in Fig 3 (e) because the OD is not bright and some area along the boundary are bright. Our presumption is that the OD is the brightest region in a normal fundus image. But with the advancement in technology and availability of superior quality fundus cameras, without any loss in generality we may assume that such images will not result in practical situations.

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References

[1] S. Tamura, Y. Okamoto and K. Yanashima, "Zerocrossing interval correction in tracking eye-fundus blood vessels", *Pattern Recognition*, Vol. 21, No. 3, 1988, pp. 227-233.

[2] Z. Liu, O. Chutatape and S. M. Krishnan, "Automatic image analysis of fundus photograph", *Proceedings of the International Conference of the IEEE Engineering in Medicine and Biology Society*, Vol. 2, 1997, pp. 524-525.

[3] C. Sinthanayothin, J. F. Boyce, H. L. Cook and T. H. Williamson, "Automated location of the OD, fovea, and retinal blood vessels from digital colour fundus images", *British Journal of Ophthalmology*, Vol. 83, No. 8, 1999, pp. 902-910.

[4] G. Zahlmann, B. Kochner, I. Ugi, D. Schuhmann, B. Liesenfeld, A. Wegner, M. Obermaier and M. Mertz, "Hybrid fuzzy image processing for situation assessment", *IEEE Engineering in Medicine and Biology*, 2000, pp. 76-83.

[5] K. Akita and H. Kuga, "A computer method of understanding ocular fundus images", *Pattern Recognition*, Vol. 15, No. 6, 1982, pp. 431-443.

[6] Hoover A. and Goldbaum M., "Locating the optic nerve in a retinal image using the fuzzy convergence of the blood vessels", *IEEE Trans. Med. Imag*, Vol. 22, pp. 951-958, 2003.

[7] Foracchia M., Grisan E. and Ruggeri A., "Detection of OD in Retinal Images by Means of a Geometrical Model of Vessel Structure", *IEEE Trans, Med. Imag*, Vol. 23, No. 10, pp. 1189-1194. 2004.

[8] Huiqi Li, Opas Chutatape, "Automatic Location of Optic Disk in Retinal Images", *Procedings of the IEEE International Conference on Image Processing*, pp. 837-840, 2001.

[9] Z. Wang and E. P. Simoncelli, "Image Quality assessment: From Error Visibility to Structural Similarity," *IEEE International Conference on Acoustics, Speech, & Signal Processing*, vol. II, pp. 573-576, Philadelphia, PA, March 2005.

[10] Aapo Hyvarinen, Juha Karhunen, Erikki Oja, "Independent Component Analysis", John Wiley & Sons, Inc, 2001.

[11] Marian Stewart Bartlett, Javier R. Movellan, and Terrence J. Sejnowski, "Face Recognition by Independent Component Analysis", *IEEE Trans on Neural Networks*, vol. 13, no. 6, November 2002.

[12] http://www.cis.hut.fi/projects/ica/fastica

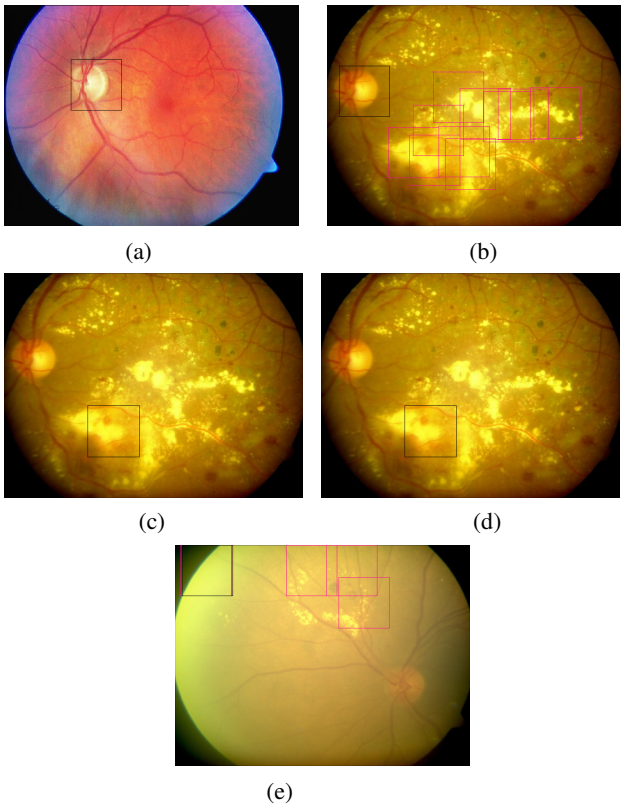

Figure 3. A sample of results: (a) OD localization on a normal retinal image by our method. (b) OD localization on a diseased retinal image by our method. (c) OD localization on the same diseased retinal image by PCA. (d) OD localization on the same diseased retinal image by ICA method based on cosines measure. (e) failure case of our method