

ANALYSIS OF RETINAL IMAGES TO DETERMINE NERVE FIBER LAYER LOSS – STRUCTURAL APPROACH

Jan Odstrčilík

Doctoral Degree Programme (1), FEEC BUT
E-mail: xodstr02@stud.feec.vutbr.cz

Supervised by: Radim Kolář

E-mail: kolarr@feec.vutbr.cz

ABSTRACT

This paper describes a structural approach to texture analysis of colour retinal photographs in order to discriminate normal and damaged glaucomatous tissue of human retina. A total number of 403 image samples of retinal tissue were used for training a simple linear classifier. The image samples were taken manually from real retina photographs by observer. The database includes 227 image samples of healthy and 176 samples of damaged tissue, respectively. The method was developed using the image samples as a standard for classifier training and finally tested on real images of retina with distinctive nerve fiber layer loss. The efficiency of the method was evaluated.

1. INTRODUCTION

Retinal nerve fiber layer (RNFL) loss is one of the most important findings for the diagnosis of glaucoma reported by ophthalmologists. However, many changes could be overlooked, especially in mass screenings, because ophthalmologists have often limited time to search for a number of different changes in retina tissue for the diagnosis of various diseases such as diabetes, hypertension and glaucoma. Therefore, the use of digital image analysis techniques can improve the results of diagnosis. Several publications concerning automated retinal image analysis were published; e.g. [4], written by Jelinek, for diagnosis of diabetic retinopathy using blood vessels segmentation approach via Gabor wavelet transform and features classification. In relation to diagnosis of hypertension we can refer article written by Wang [9]. The author evaluated certain retinal vessel changes due to the hypertension and diabetes using automated image analysis techniques via extracting some features such as bifurcation angle, artery-to-veins diameter ratio, mean artery and veins diameters, vessel tortuosity, etc. In a pilot study in 1980, Lundström and Eklundh [6] as first used retinal photographs for a computer densitometry of retinal nerve fiber atrophy. Atrophy of the RNFL can be focal (wedge – shaped) or diffuse. However, both are demonstrated by texture changes in retinal photographs. Therefore there was a high tendency to use analysis of retinal photographs for improving diagnosis of glaucoma. In relation to this purpose we can mention other article, e.g. [1]. Recently, there is an increasing interest of digital colour retinal image analysis [3].

The presented contribution is focused on a texture analysis method aimed to distinguish the healthy and the damaged tissue of the RNFL using colour retinal images taken by digital fundus camera.

2. METHOD

The image database used for the analysis contains 14 colour retinal images of healthy patients and 11 colour images of glaucomatous patients. All images were taken by fundus camera CANON CF-60UDi with embedded digital camera Canon D20. The size of images is 3504×2336 pixels and images were acquired with 60° field of view, which is a good fitting for evaluation of RNFL loss. Only green and blue channels of RGB images (their averaged values) were used for analysis because the useful part of the spectrum lies between corresponding blue and green wavelengths. The red component of RGB image does not contain any useful information. The small square image samples (41×41 pixels) were manually selected from the retinal images in the database for the texture analysis. The size of these samples was selected in order to span sufficiently large region with RNFL striation - the neural fibers are locally oriented in parallel, which causes their lightly stripy appearance. Number of 227 samples of healthy tissue of patients without glaucoma and 176 samples of damaged tissue of glaucomatous patients with focal RNFL loss were selected and included into the texture analysis method. Example of the retinal image with focal RNFL loss is depicted on Fig.1. Fig.2 shows several image samples of healthy tissue with explicit nerve fiber striations and samples of glaucomatous tissue without striations, respectively. The block diagram clearly depicting presented approach is illustrated on Fig.3.



Figure 1. a) RGB image of retina with explicit focal RNFL loss characterized by darker area in the middle of the image (next to optic disk), b) the same image obtained by averaging green and blue component of RGB.



Figure 2. a) Several image samples of healthy tissue characterized by light striations and b) several samples of glaucomatous tissue with nerve fiber loss without striations.

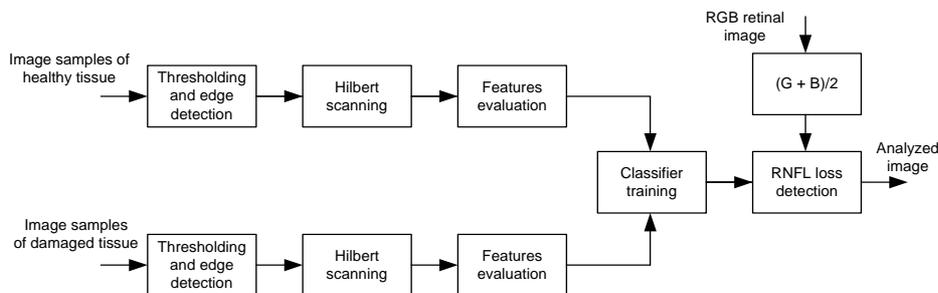


Figure 3. The block diagram of the method.

Each image sample of size 41×41 pixels is thresholded in order to obtain the binary image and edges are further detected in corresponding binarized image sample by algorithm presented in [5]. Samples are individually thresholded by gray level value G_{LS} which is determined by equation:

$$G_{LS} = k \mu_i, \quad (1)$$

where k is a constant and μ_i is a mean gray-level value within particular image sample. The constant k was empirically set by [5] to value $k = 0,9$. This was found as the best solution in order to involve all the texture primitives, which are corresponding with certain image structures – RNFL striations. Further image samples processing, crossings zeros-ones or ones-zeroes, respectively, were detected towards to obtain edges of the binary primitives. Several examples such a processed data are depicted on Fig.4.

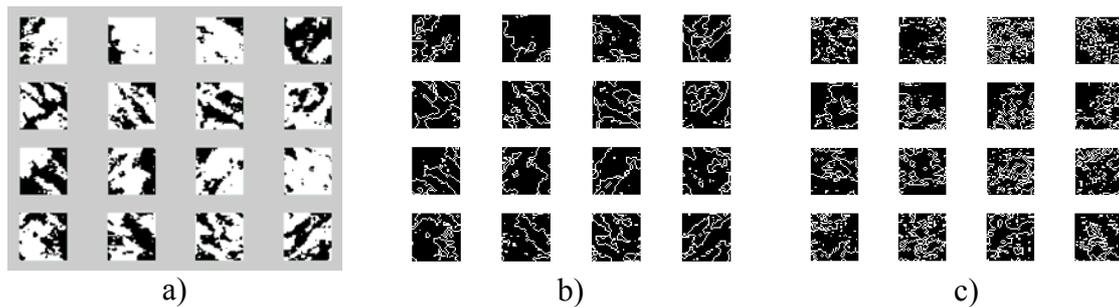


Figure 4. a) Example of binarized image samples (healthy tissue), b) edge representation of image samples of healthy and c) damaged tissue of retina, respectively.

Image samples as shown on Fig.4 b,c are represented by two-dimensional matrices. For the next step of analysis, those matrices are scanned into one-dimensional strings using coordinates determined by Hilbert curve described in [8]. The construction algorithm of the curve is clearly denoted on Fig.5.

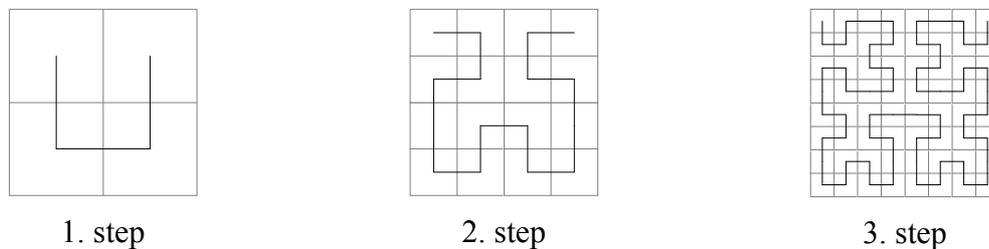


Figure 5. First three steps of Hilbert curve construction; these three steps lead to the space-filling Hilbert curve of size 8×8 , analogically we can create the curve of size 41×41 that we need for the analysis.

Each string is in addition divided into small areas of selected length. The mean value and variance is computed within each small area and total values are given by averaging those particular values. It was heuristically determined that the optimal length of small areas dividing the string is $L = 39$. For each image sample (from both groups – with healthy and damaged tissue, respectively) we obtained two features describing the texture – mean and variance. Third feature characterizing the texture is a number of binary objects directly computed from the thresholded image samples after detection of edges (Fig.4 b,c).

Those three features - mean, variance and number of objects are further used for classification with purpose to optimally decide between healthy and damaged tissue. The presented approach uses a linear classifier based on Ho-Kashyap rule that is described in [2].

3. RESULTS AND DISCUSSION

The number of 227 and 176 image samples of healthy and glaucomatous tissue, respectively, were included into the texture analysis. First, the features (mean, variance and number of objects) were computed within each edge representation of image samples. Fig.6 shows the result of the computation in features space. The blue and red clusters belong to the healthy and glaucomatous image samples. It can be seen that the both groups are well separated, which is useful for further classification.

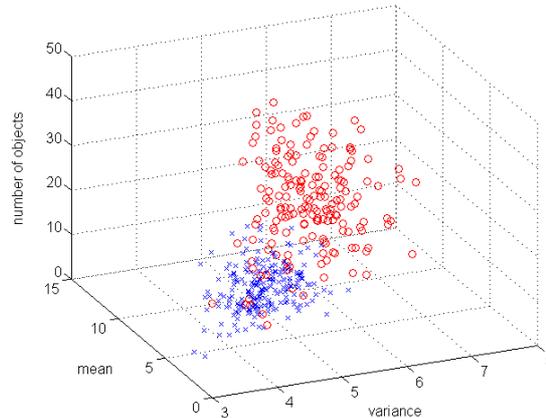


Figure 6. Depiction of features evaluation in features space.

The number of 150 image samples in database were randomly chosen and used for training the classifier. Remaining image samples in the database were used for testing. All possible combinations of features were used and classification errors were evaluated, as depicted in Tab.1. Table shows the percentual overall error (ERR) and the division of error into two categories – false positive (FP) and false negative (FN) results.

Table 1. The error of classification (P1 – mean; P2 – variance; P3 – number of objects).

P1 – P2		P1 – P3		P2 – P3		P1 – P2 – P3	
ERR = 12.07% ± 2.73		ERR = 8.43% ± 2.47		ERR = 8.38% ± 2.60		ERR = 8.60% ± 2.44	
FN=4.42%	FP=7.65%	FN = 2.46%	FP =6.03%	FN=2.30%	FP=6.08%	FN=2.59%	FP=6.01%

Furthermore, the section of the original image depicted on Fig.8a was used as an input data into the analysis. The blood vessels were masked by algorithm proposed in [7]. A small square pixel neighborhood of the same size as image samples (41×41 pixels) was scanned within the non-vessel area of the original image section pixel-by-pixel and parametric images of each feature (Fig.7 a-c) were evaluated. Higher value can be seen in the area with RNFL loss next to the optic disc. In the next step, the feature vector was created for each pixel across the parametric images and used as an input into the classifier trained by above manually selected image samples. Finally, the overall result is depicted on Fig.8b.

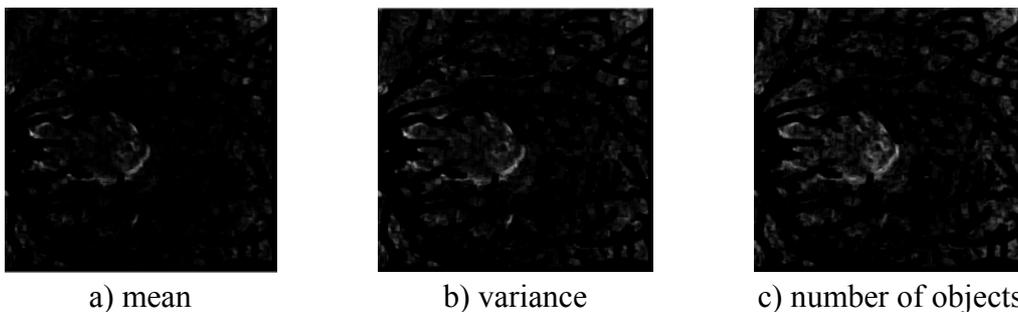
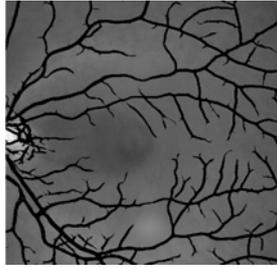
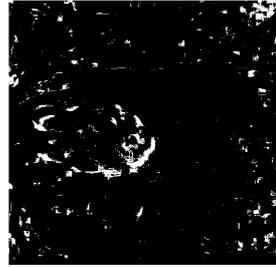


Figure 7. Parametric images of each feature.



a) original image section



b) overall result of analysis

Figure 8. Original image section and overall result of classification; the RNFL loss is situated in the middle of the image next to the optic disc.

4. CONCLUSION

The texture analysis method aimed to distinguish healthy and glaucomatous tissue of the retina was presented. The three features – mean, variance and number of objects were used as texture descriptors. The error of classification testing only manually selected image samples is approximately 8.60 % as depicted in Table 1. However, testing on the image section as shown Fig.7, 8 is not so satisfying. The RNFL loss is roughly signed and a lot of false positives are visible. For further development, the additional features describing the texture will be searched. Either combination of other texture analysis methods can be used such as statistical methods based on the Markov random fields.

ACKNOWLEDGEMENT

This work has been supported by the DAR - research center no.1M0572 coordinated by the Institute of Information Theory and Automation of the Czech Academy Science, and partly also by the institutional research frame no. MSM 0021630513, both grants sponsored by the Ministry of Education of the Czech Republic. The author highly acknowledges providing the test set of images by Eye Clinic of MUDr. Kubena in Zlin (Czech Republic).

REFERENCES

- [1] Airaksinen J. P. et al.: “Diffuse and Localized Nerve Fiber Loss in Glaucoma,” *American Journal of Ophthalmology*, vol. 98, No. 5, 1984, pp. 566-71.
- [2] Duda O. R., Hart E. P., Stork G. D.: “*Pattern Classification, second edition*,” John Wiley & Sons, Inc. New York, 2001, ISBN: 978-0-471-05669-0.
- [3] Hayashi Y. et al.: “Detection of Retinal Nerve Fiber Layer Defects in Retinal Fundus Images using Gabor Filtering,” in *Proc. of SPIE*, vol. pp. 65142Z.
- [4] Jelinek F. H.: “Automated segmentation of retinal blood vessels and identification of proliferative diabetic retinopathy,” *Journal of Optical Society of America*, vol. 24, No. 5, 2007, pp. 1448-1456.
- [5] Kolář R.: “*Methods for image analysis and pattern recognition - Application to early glaucoma diagnosis*,” Dissertation, Dpt. of Biomedical Engineering. FEEC, Brno University of Technology, Brno, Czech Republic, 2008.
- [6] Lundström M., Eklundh O. J.: “Computer Densitometry of Retinal Nerve Fibre Atrophy – a pilot study,” *Acta Ophthalmologica*, vol. 58, No. 4, 1980, pp. 639-644.
- [7] Odstrčilík J., Jan J., Kolář R., “Segmentation of vessel structure in retinal images by matched filtering,” in *Proc. BIOSIGNAL'08*, Brno, Czech Rep., June 2008, CD issue.
- [8] Petrou M.: “*Dealing with Texture*,” Wiley, London 2006, ISBN: 9780470026281.
- [9] Wang X. et al.: “Analysis of Retinal Images Associated with Hypertension and Diabetes,” *Eng. in Med. and Biol. Soc., 27th Annual Int. Conf.* 2005,1(4): 6407-6410.