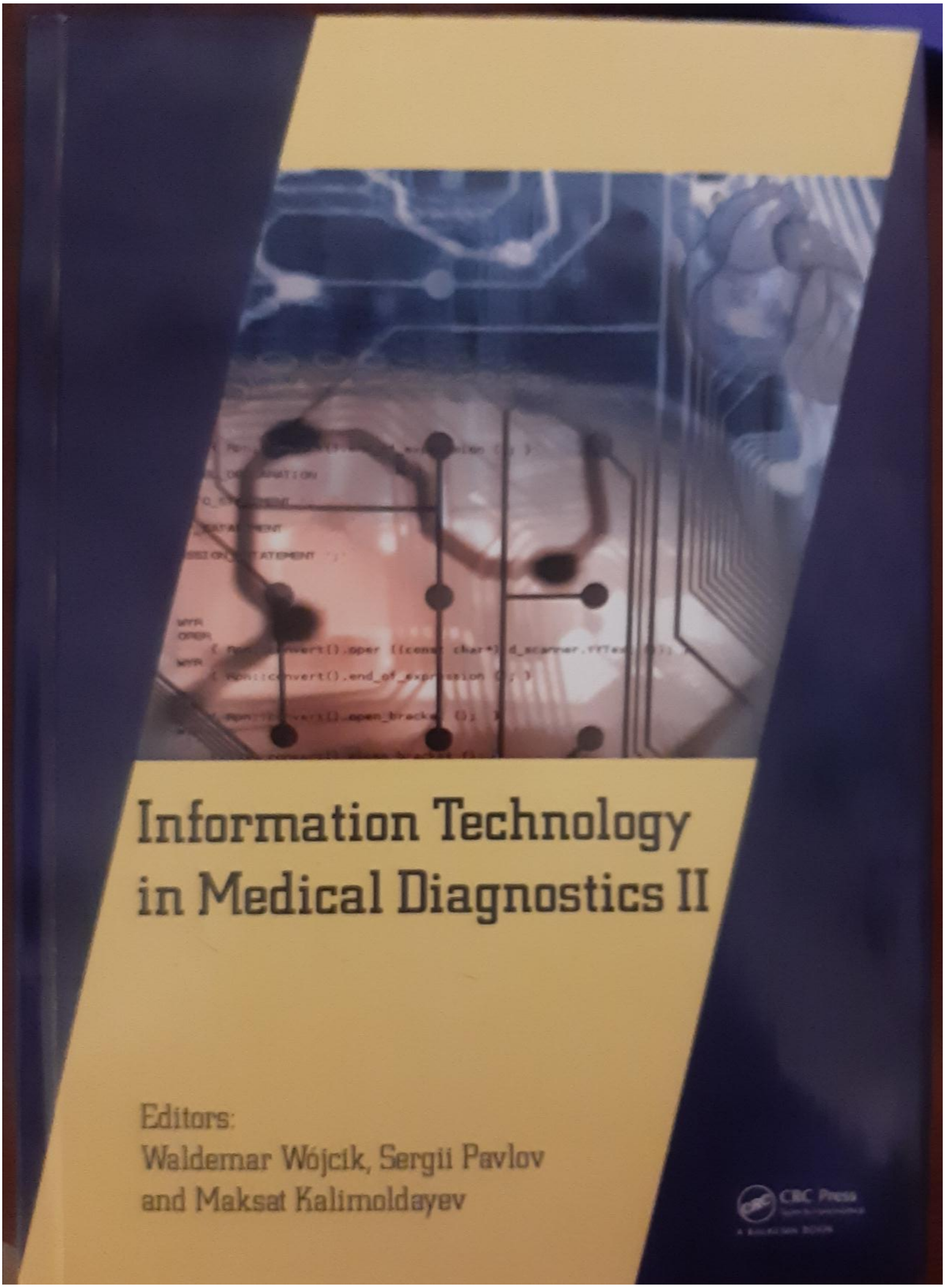
Information Technology
in Medical Diagnostics II
Editors:
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and Maksat Kalimoldayev
CRC Press

CRC Press/Balkema is an imprint of the Taylor & Francis Group, an informa business

Typeset by V Publishing Solutions Pvt Ltd., Chennai, India

Library of Congress Cataloging-in-Publication Data

Names: Wójcik, Waldemar, editor. | Pavlov, S. V. (Serhii Volodymyrovych), editor. | Kalimoldayev, Maksat, editor.
Title: Information technology in medical diagnostics II / editors, Waldemar Wójcik, Sergii Pavlov & Maksat Kalimoldayev.
Other titles: Information technology in medical diagnostics 2
Description: London, UK ; Boca Raton : CRC Press/Balkema, [2019] | Selected and extended conference papers from Polish, Ukrainian and Kazakh scientists. | Includes bibliographical references and index.
Identifiers: LCCN 2019000914 (print) | LCCN 2019002784 (ebook) | ISBN 9780429057618 (ebook) | ISBN 9780367177690 (hardcover ; alk. paper)
Subjects: | MESH: Diagnostic Techniques and Procedures | Biomedical Technology | Models, Theoretical | Congress.
Classification: LCC R857.M3 (ebook) | LCC R857.M3 (print) | NLM WB 141 | DDC 610.28--dc23
LC record available at https://lccn.loc.gov/2019000914

Published by: CRC Press/Balkema
Schipholweg 107C, 2316 XC Leiden, The Netherlands
e-mail: Pub.NL@taylorandfrancis.com
www.crcpress.com – www.taylorandfrancis.com

ISBN: 978-0-367-17769-0 (Hbk)
ISBN: 978-0-429-05761-8 (eBook)

Information Technology in Medical Diagnostics II – Wójcik, Pavlov & Kalimoldayev (Eds)

Methods and computer tools for identifying diabetes-induced fundus pathology

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ABSTRACT: This work analyses the methods and computer tools for recognition of diabetes-affected fundus images and offers the theoretical foundations for methods and computer aids for recognition of such images. The methods, algorithms and architecture of the software and hardware tools for fundus pathology identification have been developed. Experimental research has been conducted in the field of fundus image recognition and identification of pathology-affected areas.

1 INTRODUCTION

Diabetes-induced pathologies are among the major worldwide causes of poor sight and blindness and are currently the least identifiable and treatable diseases. The resultant severe pathological changes entail persistent loss of visuality functions in patients over 50 (Zolotarevskij 1997, Logay et al. 2002, Shlopak 1982, Starr et al. 1998). In recent years, such pathologies have tended to become "younger". Actually, early manifestations of diabetes-triggered fundus pathological changes are ophthalmoscopied even at the age of 12 to 20 years (Shamshinovoj 2001). It is noteworthy that a significant rise of morbidity rate is observed among the able-bodied categories of the population, inasmuch as the longevity of older people has increased, thereby increasing their share in the overall population. In the USA, fundus pathologies hold the second place, after diabetes, among the causes of blindness. In Ukraine, the situation of the extent of diabetes-induced fundus pathologies, is worsening all the time (Ferfilfain et al. 1993). For instance, over the last 20 years, the annual quantity of the first-revealed sight-disabled patients suffering from such pathology has increased 2.5 times. *The objective of this work* consists in upgrading the methods and computer tools usable for diabetes-induced fundus pathology identification.

2 REVIEW OF BIOMEDICAL IMAGE RECOGNITION METHODS AND COMPUTER TOOLS

The diagnostic image of the fundus is a network of channels (veins and arteries) shown against a background with smoothly variable brightness, which significantly overpowers the brightness of the blood vessels (Dougherty 2010, Beutel et al. 2000, Rangayyan 2005, Dougherty 2009, Rovira et al. 2016, Surtel et al. 2013). The abnormalities in an image of the fundus are any clustered black and white spots, over-tortuosity of blood vessels, or abundant ramifications of capillaries. The least perceivable yet critical criterion of a diabetes-induced fundus pathology is the condition of the vascular system. Diagnosis of a wide range of diseases involves such characteristics as the width of veins and arteries, their width ratio, lengthwise variation of blood vessel widths, time pattern of changes in the direction of blood vessels and vessel bifurcation angles (Beutel et al. 2000, Rangayyan 2005, Meyer-Base 2004, Tymkovych et al. 2017, Antonenko et al. 2017, Serkova et al. 2017). The normal fundus image and those of some fundus pathologies are shown in Fig. 1 below (Beutel et al. 2000, Rangayyan 2005, Meyer-Base 2004).

Early diagnosis automated system is an expert system used to forecast the evolution and to assess the treatment efficacy of diabetes-induced vascular diseases. The image processing engines (modules) are based on well-known algorithms. The user shell runs in the MS Windows XP operating system environment. This shell has been developed with the use of Borland Delphi 5 tools. The system database accommodates a set of reference samples and the patients' details. The information about patients includes a list of patients; a list of patients' visits to a doctor; fundus images taken in the course of each visit; and per-visit image processing results. While processing the images, the vascular areas are selected and the processing results are tabulated. Moreover, while doing so, it is possible to classify such results into several user-defined groups of vessels. The graphic user interface allows to view on the screen such things as the image under analysis (with zoom-in/out feature) (Fig. 2), the patient's details and diagnostic parameter values to be assessed, as well as the blood vessel gauge variation diagram for the given area.

The methods of research into the diabetes-induced fundus pathologies have been analysed, whereby it has been determined that the main methods of fundus structure visualisation are currently ophthalmoscopy; fundus tissue biomicrocopy; photographing of fundus

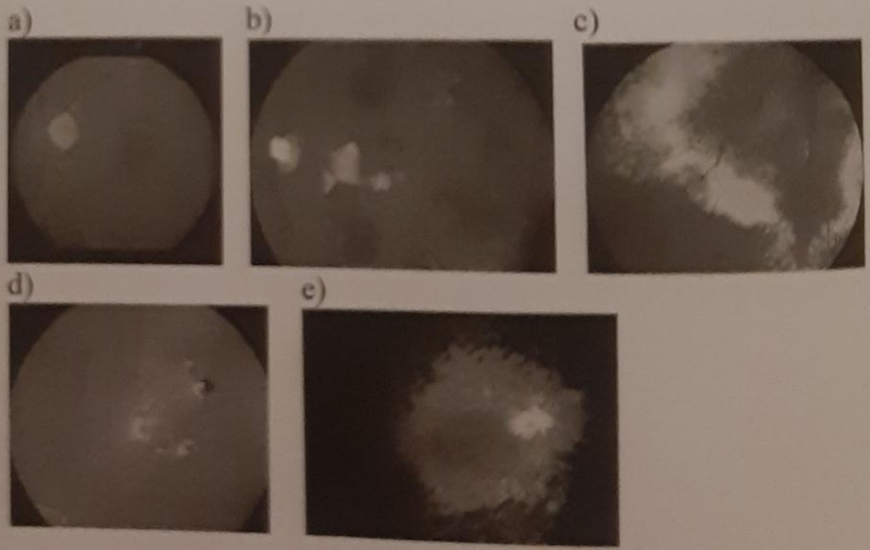

Figure 1. Images of normal fundus and some fundus pathologies: a – normal fundus; b-e – images of fundus pathologies.

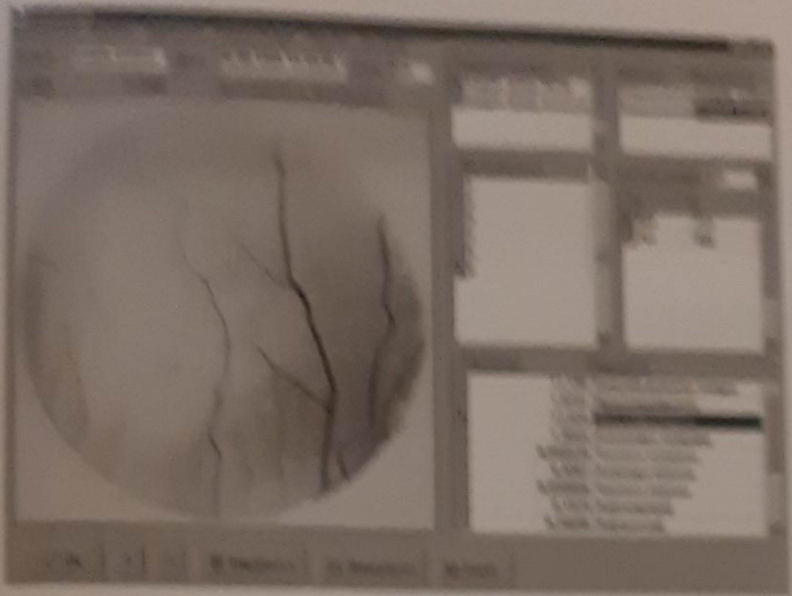

Figure 2. Diagnostic mode graphic interface.

tissues with the use of a fundus-camera; fundus fluorescent angiography with fluorescein and indocyanine green; optical coherence tomography; and laser-scanning ophthalmoscopy (Uebba 1991). All the above fundus examination methods have a common disadvantage associated with an adverse effect of eye optical system aberrations on the resolution of the devices. An analytical review of the computer-aided image recognition methods for identification of diabetes-induced fundus pathologies and their characterisation have been conducted, and it has been found out that segregation of blood vessels in fundus images is a fairly hard job in biomedical image processing, because such images are characterised by a high noise level, non-uniform brightness and the presence of patterns which look like blood vessels.

3 UPGRADING THE MATHEMATICAL FILTRATION MODEL BASED ON HALFTONE BINARISED READING OF FUNDUS IMAGES

As is well known, a human being distinguishes between four colour tones, where a verge of the main colour tone is perceived as a contrast transition (Sanniti di Baja & Thiel 1996). A 20° change influences colour perception, i.e. to achieve a perceptible change, the colour (tone) angle must change within the range from −20 to +20°, which is roughly equivalent to a quarter of the colour wheel (gamut). Hence, a low-contrast transition sector may be assumed to be 1/8 of the colour wheel. A supplementary pixel-connectivity condition may be a difference in the colour tone of no more than π/4.

Let us use a morphological segregation mathematical apparatus. Where the colour saturation decreases, the angle of perception of the adjacent colour increases, so to facilitate the analysis it makes sense to introduce a chrominance pseudo-angle:

$$\alpha = H \frac{C}{C_{max}}, \quad (1)$$

where α is a pseudo-angle; H stands for colour; C_{max} is the maximum change in saturation; C is saturation. As a result, the pixel connectivity condition may be expressed as follows:

$$W_{X,Y} = 4 \cdot 3 + 2\left[\left(m_x + m_y\right) - 4\right] \cdot 3 + \left(m_x - 3\right)\left(m_y - 2\right) \cdot 8, m_x, m_y \ge 2,$$
$$I_{x\pm 1,y} \ge I_{x,y}, \left|\alpha_{x\pm 1,y} - \alpha_{x,y}\right| \le \frac{\pi}{4}, \tag{2}$$

where $I_{x\pm 1,y}$ is the brightness of the neighbouring pixel; $I_{x,y}$ is the brightness of the current pixel; $\left|\alpha_{x\pm 1,y} - \alpha_{x,y}\right|$ is the pseudo-angle difference between the pixels.

4 DEVELOPMENT OF MATHEMATICAL MODELS FOR MEASURING THE PATHOLOGY ZONE AND THE COMPUTATION OF ITS AREA

Given that the input fundus biomedical image has been prepared beforehand and the initial data have been contoured (outlined), we can perform contour computation of the pathology zone parameters. Let us develop the mathematical models for measuring the pathology zone and computation of the area of such zone. To do so, we select the optimum geometric figures for the item being contoured. Let us create an area matrix for each selected element i:

$$M_i = \sum_{k=1}^{n} S_k, \tag{3}$$

where n is the quantity of geometric figures, $n = 3$ (triangle, circle, square); S_k is the area of each i-th selected element.

Now we have to find the similarity measure of each i-th selected element and each of the k figures. It is well known that the majority of the recognition methods use local information pertaining to image texture (Rakotomalala et al. 1998). Normally, such methods examine signs of intensity convolutions for image areas with a preset set of functions. In addition, there are also methods based on the information about an image on the whole. It is known that a phase of an image contains much more information than a spectre of such an image (Montiel et al. 1995). One of the methods relying on this fact is the method of phase correlation of images, which uses only phase-related information and is called the POC (phase-only correlation) method. The phase method explores a pair of images investigating into the differential phase behaviour of such images on the premises that this parameter characterises the similarity measure of such images. Therefore, hereinafter, we will use such a correlation parameter to find the measure of similarity between the images being compared.

The coefficient of correlation $p_{X,Y}$ between two random discrete values X, Y, with the expected values μ_X, μ_Y and mean square deviations σ_X, σ_Y is expressed as

$$p_{X,Y} = \frac{COV(X,Y)}{\sigma_X \cdot \sigma_Y}, \tag{4}$$

where $-1 \le p_{XY} \le 1$, and $COV(X,Y) = \frac{1}{n}\sum_{i=1}^{n}(x_i - \mu_X)(y_i - \mu_Y)$.

Let us find the correlation coefficient optimum value for the i-th distinguished element and each of the k figures:

$$\rho_{opt} = \max(\rho_i), \rho_{opt} \ge 0.85, \tag{5}$$

where ρ_i is the correlation coefficient for each selected area.

Thus, the mathematical model for measuring the pathology zone and computation of the area of such a zone has been developed. A correct zoom factor, as found out in the course of assessment and processing of image parameters, entails less error in measurement as compared to errors resulting from optical distortions. Having introduced the normalised criterion $\rho_{opt} \geq 0.85$, we arrive at a correct choice of the geometric figure delineating the pathology zone.

5 DEVELOPMENT OF FUNDUS CLASSIFICATION MODELS BASED ON *C-MEANS* FUZZY CLUSTERING APPARATUS

Proceeding from the analysis of the methods of computer fundus pathology image recognition, as well as from the ranging analysis of clinical implications of fundus tumour diseases (Fig. 1), it is clear that in order to classify fundus biomedical images, it is necessary to accomplish two tasks:

- singling out of the c-number of groups of fundus phenomena (items of interest);
- describing the particular features of each contoured fundus phenomenon (the coordinates, brightness, colour, width of blood vessels, angles of blood vessel branching).

It is also well known that diagnosing of eye diseases is of a probabilistic nature, which is to say that an eye pathology can be attributed to a cluster of diseases by virtue of a set of features. Here, it makes sense to use fuzzy logic mathematical apparatus. The task of the cluster analysis is to divide a certain set of items of interest (phenomena) into groups called clusters, where each cluster consists of similar items and where the items belonging to different clusters differ significantly. Such analysis implies the following objectives (Soares et al. 2006, Welk et al. 2009, Joshi & Sivaswamy 2008):

- identification of data by way of revealing the cluster structure;
- data compression; if the initial set of samples is too large, it can be reduced to a single typical representative of each cluster;
- revealing of the novelty; this implies selecting non-typical items which cannot be referred to any cluster.

Therefore, we will use the *c-means* fuzzy clustering method. The distinctive feature of fuzzy clusterisation lies in the fact that each item may belong to each cluster at a certain degree of membership. The analysis will comprise all contoured items, where the parameters will be the properties of each contoured image phenomenon (coordinates, brightness, colour, width of blood vessels, angles of blood vessel branching). As a result, the analysis yields the clusters of diseases (Joshi & Sivaswamy 2008).

Therefore, we will determine the set to be studied $M = (m_j)_{j=1}^{c}$. Let d be the number of data vectors. Matrix A determines the distance computation method. For instance, for the identity matrix we will use the Euclidean distance. The general algorithm is as follows.

1. Set the number of clusters $2 \leq c \leq d$.
2. Set the scalar metric for displaying real axis vectors.
3. Set the shutdown parameter δ.
4. Set the fuzziness factor $w \in (1, \infty)$.
5. Initialise the decomposition matrix U.
6. Compute the prototype cluster midpoints (centres) according to the formula below:

$$c_i^{(l)} = \frac{\sum_{j=1}^{d} \left(u_{ij}^{(l-1)}\right)^{w} \cdot m_j}{\sum_{j=1}^{d} \left(u_{ij}^{(l-1)}\right)^{w}}, \quad 1 \leq i \leq c. \tag{6}$$

7. For all data elements, calculate the squared distances to all cluster midpoints (centres) according to the formula below:

$$d_A^2\left(m_j,c^{(l)}\right)=\left(m_j-c^{(l)}\right)^{\prime}\cdot A\left(m_j-c^{(l)}\right). \tag{7}$$

8. Update the decomposition matrix using the formula:

$$u_{ij}^{(l)}=\frac{1}{\sum_{k=1}^{c}\left(\frac{d_A^2\left(m_j,c^{(l)}\right)}{d_A^2\left(m_j,c^{(k)}\right)}\right)^{\frac{1}{w-1}}}, \tag{8}$$

for all $1\le i\le c, 1\le j\le d$.

9. Verify the condition:

$$\left\|U^{(l)}-U^{(l-1)}\right\|<\delta. \tag{9}$$

If the condition (9) is met, complete the process; if not, resume the process starting from Step 6 with the iteration index $l = l + 1$. The objective function is determined through the formula:

$$J(M,U,C)=\sum_{i=1}^{c}\sum_{j=1}^{d}u_{ij}d_A^2\left(m_j,c^{(l)}\right), \tag{10}$$

and the set of constraints according to the formula:

$$u_{ij}\in(0,1);\ \sum_{i=1}^{c}u_{ij}=1;\ 0<\sum_{i=1}^{d}u_{ij}<d. \tag{11}$$

Let us set the number of clusters at $c = 8$, and the shutdown parameter at $\delta = 0.5$. The fuzziness factor w is established by each physician experimentally for selecting the optimum option of eye pathology clusterisation. In the course of assessment of the characteristics of each contoured image item, the division is carried out with respect to the largest numbers (which entails the highest error in terms of the Euclidian distance). To reduce such error, let us resort to normalisation. This will yield atypicality in terms of all equal-weight factors, which is required for optimal clusterisation of pathologies.

6 COMPARATIVE EFFICIENCY ANALYSIS OF FUNDUS IMAGE RECOGNITION MODELS

An important factor influencing the selection of the recognition algorithm is its performance efficiency factor. It implies precision in outlining the items of interest in fundus biomedical images. Such comprehensive factor may be a mean square error criterion combined with a criterion of minimum empirical distance between a perfect (reference) outline picture and the contours obtained as a result of upgrading the technique of multi-grade image generalisation with W spatial-bond spectre through the application of the morphological segmentation method.

Segmentation brings about two types of errors: in a segmented picture a point is shown as that belonging to the contour while in a perfect outline picture such point does not belong to the contour; or in a segmented picture a point is shown as that not belonging to the contour, whereas in a perfect outline picture such point does belong to the contour. Therefore, in assessing the quality of segmentation, we have to use two criteria:

- the criterion which indicates the degree of similarity between the segmented picture and the perfect outline picture (FOM);
- the criterion which signifies the degree of difference thereof (RMS).

The FOM (Figure of Merit) criterion stands for the empirical distance between the perfect outline picture which is represented by contours and the segmentation-resultant contours g (Nagashima et al. 2009). The RMS (Root Mean Squared Error) criterion is a mean square error. To assess the quality of the algorithm developed by its authors, the algorithm has been compared to such well-known operators as Roberts operator, Prewitt operator, Sobel operator and Canny operator. The Delphi environment has been used to model the performance of the well-known segmentation algorithms. 500 images have been used as test pictures and perfect outline pictures (offered by the experts).

For an example of a test picture (a), perfect outline picture (b) and the segmentation results with the use of the algorithm developed by its authors (c), as well as with Roberts operator (d), Prewitt operator (e), Sobel operator (f) and Canny operator (g), see Figure 3.

As is clear from Figure 3 above, the algorithm in question ensures the most precise outlining, as compared to the well-known techniques, which is confirmed both by the visual assessment of the resultant images and by the computed FOM and RMS criteria (Nagashima et al.

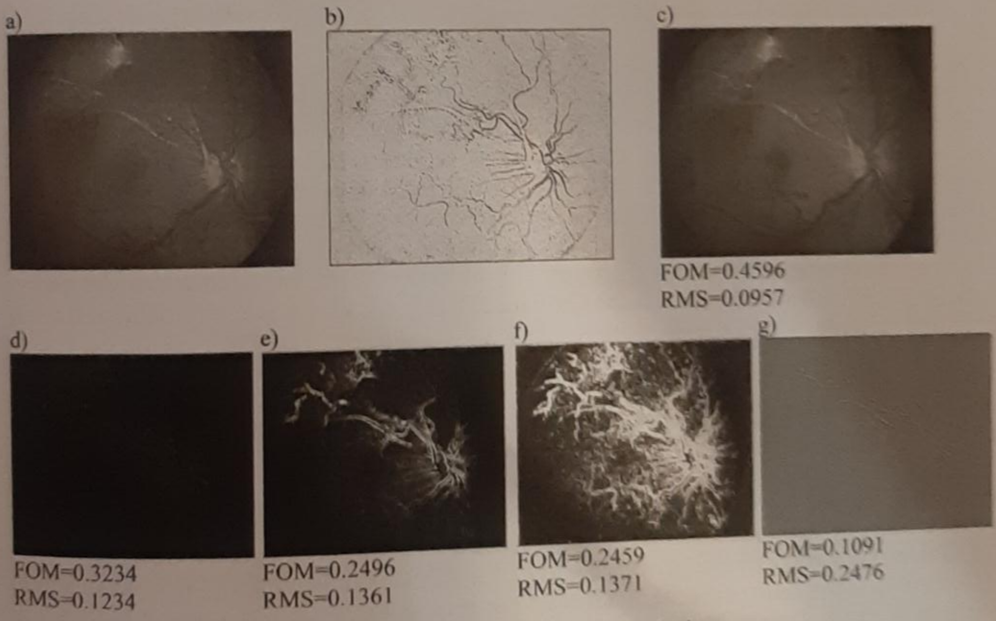

Figure 3. Example of segmentation with the use of different methods.

Table 1. FOM and RMS average estimated criteria.

Criterion	Method in question	Roberts operator	Sobel operator	Kirsch method	Wallis operator
FOM	0.2504	0.2380	0.2073	0.1902	0.2071
RMS	0.2465	0.2225	0.2459	0.3385	0.2451

2009), Trubin et al. 2008, Petrov & Medvedeva 2008, Levashkina & Porchev 2009). Table 1 below shows the average estimated FOM and RMS criteria obtained for 500 images through application of the segmentation method in question and well-known methods.

Therefore, the segmentation algorithm developed by its authors is easily feasible, requires little computation and is not inferior to the well-known algorithms, such as those developed by Roberts, Prewitt, Sobel and Canny, in terms of precision of contour identification of the items of interest.

7 DEVELOPMENT OF A COMPUTER RECOGNITION METHOD FOR DIABETES-INDUCED FUNDUS PATHOLOGY

The task of pathology recognition consists in the following. Automatic tracing of an individual blood vessel is carried out from a user-set starting point to an end point in the direction of the blood vessel as found out in the current point. The width of a blood vessel is defined as a quantity of non-zero counts on a line which is perpendicular to the direction of the blood vessel. After the width is determined, the starting point is shifted by a certain user-set tracing increment in the direction which is found out from among the pre-computed directions as the one closest to the direct line towards the end point. Such tracing process generates a sequence of parameters which characterise the condition of the vascular system and can be used for pathology assessment.

8 DEVELOPMENT OF COMPUTER SYSTEM ARCHITECTURE

The computer system is a combination of two major components: the hardware and the software. The hardware component includes graphic processing units (GPU) and an external fundus image acquisition device (fundus camera). The software consists of the image enhancement unit (IEU), image analysis unit (IAU) data unit (DU). The computer system is implemented in Borland's DELPHI environment. In terms of hardware, the system must incorporate a graphics adapter with a pixel-shading feature. This computer system is intended for ascertaining the location and the area of a pathology, as well as for clusterisation and diagnosing of fundus pathologies. For the hardware platform, it has been decided to use an nVidia video card based on the GeForce 250 chipset, which is an affordable and fairly efficient solution.

9 RESULTS OF EXPERIMENTAL RESEARCH INTO PATHOLOGY LOCALISATION AND PATHOLOGY AREA ASSESSMENT

The database for the experimental research was furnished by Filatov Eye Pathology and Tissue Therapy Research Institute of the Academy of Medical Science of Ukraine. It contains over 500 images obtained with the use of a ZEISS VISUCAM LITE fundus camera (Germany). Upon enhancing the quality and pre-processing of such an image, it is necessary to analyse its parameters. Having delineated the contours of the image items of interest (entities), we arrive at the respective fundus outline pictures (EGOPs). The next step is to identify all items so outlined for existence of a pathology, if any, and for its area. Table 2 below shows the results of identification of item-related parameters in the input test picture, as seen in Figure 4. Table 3 below, shows the results of localisation of pathology and assessment of its area.

The analysis of the results demonstrates that the bulk-information-based segmentation method, relying on assessment of the quantity of information, as developed by its authors, exceeds by 5 to 25% in terms of the FOM criterion, and is not much inferior, in terms of RMS criterion, to the Roberts, Prewitt and Sobel operators.

Table 2. Item-of-interest related parameter identification results in the above input test picture.

Item	X midpoint coordinate	Y midpoint coordinate	Area [mm²]
1	46	25	28.4
2	48	15	5.5
3	63	7	10.7
4	66	22	19.3
5	72	13	19.6
6	76	9	3.1
7	87	23	26.4
		Total area	**113.0**

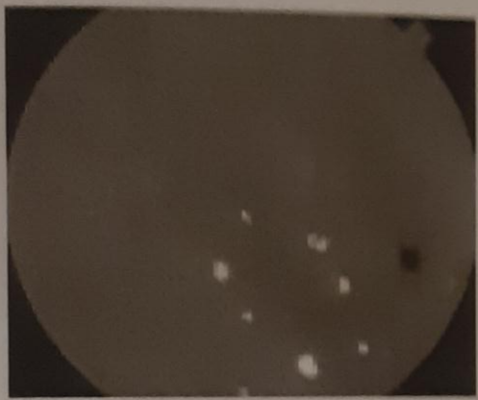

Figure 4. Input test picture.

Table 3. Results of experimental research in localisation of pathology and assessment of its area.

Picture [mm²]	Pathology zone area [mm²]	Total area [mm²]	Pathology [%]
1	2.0	3.0	4.00
1	154.3	6486.5	2.38
2	1398.0	5929.0	23.58
3	711.2	6404.0	11.11
4	1138.5	6446.0	17.66
5	1381.3	5632.5	24.52
6	1047.0	6445.5	16.24
7	703.4	6437.0	10.93
8	1490.0	6488.0	22.97
9	133.6	6471.0	2.06
10	113.0	6387.5	1.77
11	1184.7	6197.5	19.12
12	968.3	6261.5	15.46
13	1224.5	6397.5	14.45
14	864.8	6452.0	13.4
15	922.0	6392.5	14.42
16	694.0	5814.5	11.94
	Average pathology		**13.88**

10 RESULTS OF EXPERIMENTAL RESEARCH INTO [illegible] OF FUNDUS PATHOLOGIES

Upon outlining of the image items of interest (entities), acquisition of [illegible] and assessment of the area of pathologies, it is necessary to perform clustering [illegible] ing of such fundus pathologies. In practical ophthalmology, the following [illegible] deemed to be clinical implications of pathology:

- location of an item in question (post-equatorial location, equatorial location, [illegible] within the disk of optic nerve, etc.);
- colour (black, pigment-free, pink etc.);
- size (diameter, height).

Proceeding from Table 2 above, let us sum up the data for pathology cluster analysis [illegible] tabular form (Table 4). To reduce the measurement error, let us use normalisation. [illegible] yield atypicality in terms of all equal-weight factors, which is required for optimal [illegible] tion of pathologies (Table 5). For the results of diabetes-induced fundus pathology [illegible] sation see Table 6 below.

To assess the efficiency of the fuzzy logic based method, a dispersion criterion [illegible] exhibiting the sum of distances from the items of interest to the cluster midpoints at a certain degree of membership (Ritter & Wilson 1996, Archangelskiy 2006).

$$J = \sum_{i=1}^{[illegible]} \sum_{j=1}^{n} (m_{ij})^{w} \, dist(v_i, d_j), \quad [illegible]$$

where $dist(v_i, d_j)$ is the Euclidian distance between j-th item $d_j = [illegible]$ and cluster midpoint $v_i = (v_{i1}, v_{i2}, \ldots, v_{in})$; $w \in (1, \infty)$ is the exponential weight which determines fuzziness or blurriness of clusters.

Table 4. Input data for pathology cluster analysis.

Item of interest	Item location	Colour	Size [mm]
1	Equatorial	Yellow	6.0
2	post-equatorial	White	2.6
3	post-equatorial	White	3.7
4	post-equatorial	White	4.9
5	post-equatorial	Yellow	4.9
6	post-equatorial	Yellow	1.9
7	post-equatorial	Black	5.8

Table 5. Normalised data for pathology cluster analysis.

Item of interest	Item location	Colour	Size [mm]
1	1.00	0.39	1.00
2	0.60	0.00	0.43
3	0.28	0.00	0.62
4	[illegible]	0.00	0.82
5	0.52	0.00	0.82
6	0.36	0.00	0.32
7	0.92	0.99	0.97

Table 6. [illegible]

Item 1	Item 2	New cluster	Distance
[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	10	[illegible]
[illegible]	[illegible]	11	[illegible]
10	[illegible]	12	[illegible]
11	12	13	[illegible]

Table 7. Experimental research estimated results for fundus pathology clusterisation

Method	Estimated dispersion	Estimated dispersion of pre-set number of clusters (with linguistic parameters)	Estimated dispersion of pre-set number of clusters (with linguistic parameters)	Mean estimated value
Kohonen	0.648	0.831	0.831	[illegible]
k-means		0.743		[illegible]
c-means	1.000	0.960	1.000	[illegible]

$$V = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1n} \\ v_{21} & v_{22} & \cdots & v_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ v_{c1} & v_{c2} & \cdots & v_{cn} \end{bmatrix}, \qquad (13)$$

and $c \times m$ is the matrix of cluster midpoint coordinates, where the elements of such a matrix are found according to the formula below:

$$v_{kj} = \frac{\sum_{i=1}^{n} (m_{ki})^{\beta} d_{ij}}{\sum_{i=1}^{n} (m_{ki})^{\beta}}, \; k = \overline{1,m} \qquad (14)$$

Having found the dispersion criterion J, we can assess the efficiency of the fuzzy logic-based method for diabetes induced fundus pathology clusterisation (see Table 7 above). The pathology average percentage is 13.88%. In the course of the above-said research, the clusterisation method has demonstrated the best result ([illegible]), which testifies to the applicability of such a method for biomedical image recognition, as well as to its adaptability for other fields of application.

11 CONCLUSIONS

1 The filtration mathematical model has been *upgraded* on the basis of halftone binarised counts of fundus image preparations and through the use of morphological segregation mathematical apparatus and introduction of a chrominance pseudo-angle. The analysis of the results demonstrates that the segmentation method, based on assessment of the quantity of information, as developed by its authors, exceeds by 5 to 25% in terms of the FOM criterion, and is not much inferior, in terms of RMS criterion, to the Roberts, Prewitt and Sobel operators.

2. The authors have *pioneered* in developing a mathematical model for measuring the pathology zone and computation of its area with the use of a choice of optimum geometric figures to match the items being contoured. Having introduced the normalized criterion $\delta_{2n} \geq 0.85$, we are able to select the best geometric figure to delimit the pathology zone area.
3. The model of clusterisation of diabetes-induced fundus pathology images has been further *improved* on the basis of the c-means fuzzy clustering apparatus. To reduce the measurement error, we have used normalization, which yields atypicality in terms of all equal-weight factors, which is required for optimal clusterisation of pathologies.
4. We have *further elaborated* the fundus image computer recognition method based on phase correlation of images, which contributes to better fundus image recognition inasmuch as a phase of an image contains much more information than a spectre of such an image.
5. The authors have *developed* the software tools and have *offered* the optimum hardware architecture incorporating an nVidia video card based on the GeForce 230 chipset, which is an affordable and fairly efficient solution. Based on the results of our research, we have upgraded the computer system, whereby sorting the results inside a data block passes over to a GPU, thus reducing by tens of times the quantity of the output data arrays (64 to 256 times depending on the rank field size).
6. The computer system architecture *has been developed*.
7. Experimental research has been conducted into localisation of pathology and assessment of its area, as well as a cluster analysis of diabetes-induced fundus pathologies has been performed. The pathology average percentage is 13.88%. In the course of the research, the clusterisation method has demonstrated the best result (0.996%), which testifies to the applicability of such a method for biomedical image recognition, as well as to its adaptability for other fields of applications.

REFERENCES

Antonenko, Y.A., Mustetsov, T.N., Hamdi, R.R., Malecka-Massalska, T., Orshubekov, N., Dzierżak, R., and Uvaysova, S. 2017. "Double-compression method for biomedical images." *Proc. SPIE* 10445.

Archangelskiy, A. 2006. *Priyomi programmirovaniya v Delphi na osnove VCL*. M.: «Binom-Press».

Beutel, J., Kundel, H.L., and Van Metter, R.L. 2000. *Handbook of Medical Imaging*. Washington: Bellingham.

Dougherty, G. 2009. *Digital Image Processing for Medical Applications*. Cambridge: Cambridge University Press.

Dougherty, G. 2010. "Image analysis in medical imaging: recent advances in selected examples." *Biomed Imaging Interv J* 6(3): 32.

Terfiliain, I.L., Kriganovskaja, T.B., Altfanova, T.A., and Povechenko, U.L. 1993. "Sosudistaja patologija glaza kak prichina invalidnosti na Ukraine." *Tezis dop. VIII mizgnar. konf. oftalmologiv* 201–202.

Joshi, G. D., and Sivaswamy, J. 2008. "Colour Retinal Image Enhancement based on Domain Knowledge." *Sixth Indian Conference on Computer Vision, Graphics and Image Processing (ICVGIP)*: 591–598.

Levashkina, A.O., and Porchev, S.B. 2009. "Sravnitelnij analiz supervizornich kriteriev ochenki kachestva segmentacii izobrajeniy." *Informacionnie technologii* 3: 52–57.

Logay, I.M., Serguenko, N.M., and Krujanovskaya, T.B. 2002. "Slepota i slabovidene v Ukraine i aktualnue voprosu ee profilaktiki." In *Tezis dop. X z'izdy oftalmol* Odesa, 10–11. Ukraine: Astroprint.

Meyer-Base, A. 2004. *Pattern Recognition for Medical Imaging*. San Diego, CA: Elsevier Academic.

Montiel, M.E., Aguado, A.S., and Garza-Jinich, M.A., et al. 1995. "Image manipulation using M-filters in a Pyramidal computer model." *IEEE trans. on pattern analysis and machine intelligence* 17(11): 1110–1115.

Nagashima, S., Ito, K., Aoki, T., Ishii, H., and Kobayashi, K. 2009. "High Accuracy Estimation of Image Rotation using 1D Phase-Only Correlation." *IEICE Trans. Fund.* E92-A: 235–243.

Petrov, E.P., and Medvedeva, E.B. 2008. "Vichislenie statisticheskoj izbitochnosti stayticheskix izobrajenij." *Voprosi radioelektroniki* 3: 76–83.

Rakotomalala, V., Macaire, L., Postaire, J.-G., and Valette, M. 1998. "Identification of retinal vessels by color image analysis." *Machine graphics & vision* 7(4): 725–743.

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For many centuries, mankind has tried to learn about his health. Initially, during the pre-technological period, he could only rely on his senses. Then there were simple tools to help the senses. The breakthrough was turned out to be the discovery of X-rays, which gave insight into the human body. Contemporary medical diagnostics are increasingly supported by information technology, which for example offers a very thorough analysis of the tissue image or the pathology differentiation. It also offers possibilities for very early preventive diagnosis. Under the influence of information technology, 'traditional' diagnostic techniques and new ones are changing. More and more often the same methods can be used for both medical and technical diagnostics. In addition, methodologies are developed that are inspired by the functioning of living organisms.

Information Technology in Medical Diagnostics II is the second volume in a series showing the latest advances in information technologies directly or indirectly applied to medical diagnostics. Unlike the previous book, this volume does not contain closed chapters, but rather extended versions of presentations made during two conferences: XLVIII International Scientific and Practical Conference 'Application of Lasers in Medicine and Biology' (Kharkov, Ukraine) and the International Scientific Internet conference 'Computer graphics and image processing' (Vinnitsa, Ukriane), both held in May 2018.

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CRC Press