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An improved matched filter for blood vessel detection of digital retinal images

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Abstract

The matched filter has been widely used in the detection of blood vessels of the human retina digital image. In this paper, the matched filter response to the detection of blood vessels is increased by proposing better filter parameters. These filter parameters are found by using an optimization procedure on 20 retina images of the DRIVE database. Comparisons with other approaches show that the matched filter that uses the newly found parameters outperforms the matched filter that uses the classical filter parameters as well as some vessel detection techniques. A technique is also discussed to find the best threshold value for the continuous matched filter output image and hence the best segmented vessel image.

Keywords: Matched filter; Retina image; Digital image; DRIVE; Retinopathy; Vessel detection

1. Introduction

Retinal images of humans are used in the diagnoses of diseases by ophthalmologist [1–5]. To build an expert system that is able to perform the diagnoses task we need to use digital retinal images. By imaging the retina of a person with a special camera, then using image processing and pattern recognition techniques to analyze that retina we can make a specific diagnoses decision. One of the important operations performed on the digital retina is the edge detection of blood vessels of the retina. A specialized edge detection technique may be needed since traditional edge detection techniques (Sobel, Prewwit, Canney, etc.) might not be able to accurately segment the vessels from the background of the retina image. Many methods, however, have been proposed for this purpose; matched filter [1], morphology edge detection [6], ridge-based vessel segmentation [7] which is called pixel classification in [8], and wavelet transform [9]. Performance measures on those proposed techniques showed that nearly all techniques outperforms that of the matched filter method [7].

The matched filter method has some parameters governing its detection process [1,2,10]. The values of matched filter parameters were proposed in [1] and have been used since then in all other works for applications and comparisons. Some methods, as in [11], proposed to improve the thresholding (and hence the segmentation) of the matched filter output image but the matched filters parameters were never changed. In [12], the second order Gaussian matched filter is proposed for the detection of blood vessels. Hough transform have been used in [13] to detect blood vessels. In this work, we use an optimization method to adjust the matched filter parameters with a hope that the performance of the matched filter will increase. The optimization procedure is performed by comparing the each edge detected image to a reference hand labeled image to judge the filter parameters. The segmentation of blood vessels is also discussed by using morphological image processing tools.

2. The matched filter

The matched filter is one of the template matching algorithms that is used in the detection of the blood vessels in retinal images and other application as well. It is based on the spatial properties of the object to be recognized. The idea of the matched filter is introduced by taking a number of samples for a cross section of retinal blood vessels, the gray level profile of these samples is then approximated by a Gaussian shaped curve. Fig. 1 shows

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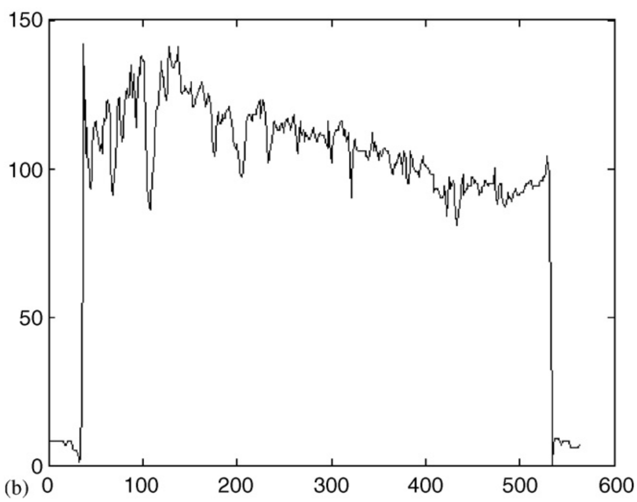

Fig. 1. The green band of a digital retina image. (b) Profile of a one pixel width at the 200th row of the retina image shown in (a).

an original image of the retina and gray level profile of some cross section of that image.

Matched filter designing is based on a number of properties for blood vessels

- Vessels can be approximated as anti parallel segments.
- Vessels have lower reflectance than other retinal surfaces, so they appear darker relative to the background.
- Vessel size may decrease when moving away from the optic disk, the width of a retina vessel may lie within the range of 2–10 pixels.
- The intensity profile varies by a small amount from vessel to vessel.
- The intensity profile has a Gaussian shape.

The matched filter kernel may be expressed by (see [1] for details):

$$k(x, y) = -\exp(-x^2/2\sigma^2) \quad \forall\ |y| \leqslant L/2, \tag{1}$$

where L is the length of the vessel segment that has the same orientation, σ defines the spread of the intensity profile. To be able to detect vessels on all possible orientations, the kernel must be rotated to all possible vessel orientations and the maximum response from the filter bank is registered. Many papers found that rotating by an amount of 15° is adequate to detect vessels with an acceptable amount of accuracy which results a filter bank with 12 kernels. The authors of [1] made some experiments on the values of L and σ and found that the best parameter values were those that gave the maximum response at $L=9$ and $\sigma=2$. They did not, however, present their experiments of finding L and σ.

A Gaussian curve has infinitely long double sided trails; the trails are truncated at $u = \pm 3\sigma$. A neighborhood N is defined such that

$$N = \{(u, v), |u| \leqslant T, |v| \leqslant L/2\}, \tag{2}$$

where $T = 3\sigma$. Let p_i be the points that belongs to the neighborhood N given as

$$p_i = [u \;\; v] = [x \quad y] \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix}. \tag{3}$$

The corresponding weights in the kernel i ($i = 1, \ldots, 12$ which is the number of kernels) are given by

$$k_i(x, y) = -\exp(-u^2/2\sigma^2) \quad \forall p_i \in N. \tag{4}$$

The filter is normalized to have zero mean as follows:

$$k_i'(x, y) = k_i(x, y) - m_i, \tag{5}$$

where $m_i = 1/a\sum_{p_i \in N} k_i(x, y)$, and a denotes the number of points in N.

3. Improving the matched filter response

To improve the performance of the matched filter we believe that we need to find better parameters for L, σ, and T. The optimization program is simple in which we use an exhaustive search for the best parameters for L, σ, and T. The search space is not very large since we limit the values of those parameters to $L = \{7, 7.1, 7.2, \ldots, 11\}$, $\sigma = \{1.5, 1.6, 1.7, \ldots, 3\}$, and $T = \{2, 2.25, 2.5, \ldots, 10\}$. Let the input retina image be f and the output filtered image be $f_{L\sigma T}$. To decide that a filtered image is good or bad, it is thresholded according to [14] yielding $g_{L\sigma T}$ and then compared to a corresponding hand labeled retina h image. The hand labeled image is obtained from a retina image by an experienced observer to be used for comparison purposes [7]. The comparison yields true pixels (pixels detected as vessels and they appear as vessels in the hand label) and false pixels (pixels detected as vessels yet they appear as non-vessels in the hand label). The true_ratio is obtained by dividing the true pixels by the number of vessel pixels in h, and the false_ratio is obtained by dividing the false pixels by the number of non-vessel pixels in h. The quality factor used to judge whether that image is good or bad is as follows:

$$Q_{L\sigma T} = true\_ratio - false\_ratio. \tag{6}$$

The maximum $Q_{L\sigma T}$ means that the filter with the corresponding L, σ, and T gives the highest response. It might be useful to operate this optimization procedure on many images and if L, σ, and T values are repeated for all or most of the images, we deduce that those filter parameters are the best ones.

4. Experimental results

To find the best matched filter parameters, the optimization is implemented on the DRIVE database [7]. This database contains 40 digital retinal images along with their corresponding hand label. The DRIVE images are colored RGB images and in all experiments we shall use the green band since it has the most reliable vessels (as proposed in the previous works [1,6]). All hand labels of the DRIVE were obtained by an experienced pathologist. Every optimization procedure is performed on the 20 train images of the DRIVE. The filter parameters that appear as the first and second rank (the highest quality factor) are listed in Table 1.

Now that we obtained the best parameters for the matched filter, it is appropriate to test the improved matched filter on three performance measures commonly used to compare the detection of blood vessels. The first is receiver operating curve (ROC) used to plot the variation of false ration versus true ratio. The second is the area under the ROC, the higher the area the better the detection; if the area under ROC is one this means perfect detection. The ROC is obtained as follows:

(1) Let the input retina image be f and the matched filter output image be $f_{L\sigma T}$ (which is a continues image). By thresholding $f_{L\sigma T}$ via different threshold values from 0 to 1 in a step of 0.001 (that is if we talk about normalized intensity) we obtain several binary images, each image corresponds to a certain threshold.
(2) We then calculate the true_ratio and the false_ratio for each of the binary images. This ROC is found for one image in the DRIVE database; we repeat the calculation and obtain the average ROC for the 19 remaining images. The resultant curve is shown in Fig. 2 in comparison with other methods.

The third measure is the maximum accuracy average (MAA), which takes the average accuracy for all images. The accuracy for one image is calculated by taking the sum for the total number of pixels, correctly classified as vessel and non-vessel pixels at a specified threshold, and dividing the sum by the total number of pixels in the field of view (FOV) which is a circular area of the retinal image. To determine whether a vessel is classified correctly or not, the vessel image is compared to the corresponding hand labeled image.

Table 1
The number of repetitions of the Gaussian matched filters in the optimization program out of 20 cases

L, σ, T	No. of repetitions out of 20	Average quality factor
10.8, 1.9, 8	10	0.7397
2.3, 10.6, 8	5	0.7247

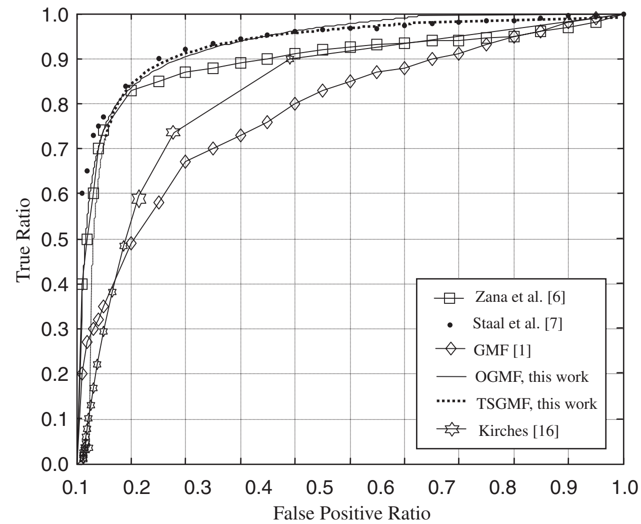

Fig. 2. The average ROC area for the 40 DRIVE images using six different methods.

Table 2
A comparison with other methods of the matched filter using the optimum parameters found in this work

Vessel detection method	Average ROC area	MAA	Time needed to vessel detection of one image in seconds
OGMF (this work)	0.9352	0.9458	5.5 s on a 1.6 GHz PC
TSGMF (this work)	0.9435	0.9535	11 s on a 1.6 GHz PC
Staal et al. [7]	0.9520	0.9611	900 s on a 1 GHz PC
GMF [1]	0.7878	0.8773	5 s on a 1.6 GHz PC
Kirsch [16]	0.8300	0.9151	2 s on a 1.6 GHz PC
Zana and Klein [13]	0.8984	0.9377	NA

In Fig. 2, GMF is the original Gaussian matched filter with its original parameters $(L, \sigma, T) = (9, 2, 6)$ as proposed in [1], OGMF is the optimized Gaussian matched filter with parameters $(L, \sigma, T) = (10.8, 1.9, 8)$, TSGMF is the two stage Gaussian matched filter that has the parameters $(L_1, \sigma_1, T_1) = (10.8, 1.9, 8)$ and $(L_2, \sigma_2, T_2) = (7.6, 1.9, 8)$ such that the filter bank is consisted of 24 filters and the maximum response is retained. Table 2 provides the comparison of different methods with the proposed improved matched filter.

Another comparison is performed on another publicly available database which is Hoover [11], see Table 3.

Our next experiment is verifying that the green band of a digital retinal image is more appropriate than other bands. In this case, we implemented the improved matched filter with parameters $(L, \sigma, T) = (10.8, 1.9, 8)$. From the results shown in Table 4 we can see that the performance of the red and the blue band are comparable to the green band.

Table 3
Two sets of matched filter parameters implemented on DRIVE and Hoover databases

Database	L, σ, T			Average ROC area	MAA
DRIVE	10.8	1.9	8	0.9352	0.9458
Hoover	10.8	1.9	8	0.9090	0.9467
DRIVE	10.6	2.3	9	0.9328	0.9441
Hoover	10.6	2.3	9	0.9077	0.9385

Table 4
Comparison of the average ROC area of 20 DRIVE retina images for the matched filter

Band	Average ROC area
Red	0.9348
Blue	0.9339
Green	0.9352

Each experiment is performed on one band, i.e., on red, blue, and green bands. This comparison shows the response of the matched filter to different bands.

Another issue to be discussed here is the threshold value to be used to obtain a binary segmented image ready for further retina analysis. We may simply think of using the average of thresholds that yielded the maximum accuracy. Then, this threshold can be used to automatically binarize any continuous image resulted from a matched filter. The below table list some experiments to determine the average threshold, and then using that threshold to find a binary image and calculate its accuracy. According to the results shown in Table 5, the average threshold is 0.6675. This should be used with the matched filter that has the values $(L, \sigma, T) = (10.8, 1.9, 8)$.

An automated method to find the best threshold is better than the above that depends on the average threshold. We developed an automated method that is based on the number of connected components and Euler number [15]. The image output from the matched filter is continuous so we need a threshold to segment the vessels. We expect that the best segmented image should (or may) have the minimum number of connected components since the vessel appears as a vascular shaped. Our experiments revealed that the best threshold may be found at the first local minima of the number of connected component provided that the Euler number is positive. If the number of connected components is decreasing as the threshold is increased then we look for the first local minima in Euler numbers. If both are decreasing we may consider the average value computed as shown in the above experiment (for a certain filter). In all our experiments on the DRIVE, the first condition applies to 95% of the cases. The result is shown for the first image in the DRIVE using the two stage matched filter.

From the Table 6, we can see that the image with threshold 0.65 is the best segmented image. It is worth mentioning that 19 remaining images have the same property as shown in Table 6 of the first image. Thresholds and accuracies, however,

Table 5
Determining the average threshold for the matched filter with $(L, \sigma, T) = (10.8, 1.9, 8)$

Image number	Maximum accuracy	Threshold at maximum accuracy	Accuracy at average threshold (0.6675)	Error rate between the MA and accuracy calculated at the average threshold
1	0.9507	0.65	0.9509	0.0002
2	0.9506	0.70	0.9499	0.0007
3	0.9458	0.55	0.9404	0.0054
4	0.9454	0.70	0.9454	0.0000
5	0.9426	0.50	0.9372	0.0054
6	0.9411	0.55	0.9379	0.0032
7	0.9364	0.75	0.9348	0.0016
8	0.9313	0.65	0.9310	0.0003
9	0.9413	0.65	0.9411	0.0002
10	0.9454	0.55	0.9438	0.0016
11	0.9350	0.80	0.9309	0.0041
12	0.9415	0.65	0.9414	0.0001
13	0.9398	0.65	0.9397	0.0001
14	0.9521	0.75	0.9511	0.0010
15	0.9501	0.85	0.9474	0.0027
16	0.9386	0.70	0.9385	0.0001
17	0.9448	0.75	0.9418	0.0030
18	0.9437	0.75	0.9424	0.0013
19	0.9536	0.60	0.9531	0.0005
20	0.9477	0.60	0.9468	0.0009
Mean	0.9439	0.6675	0.9422	0.0016
Standard deviation	0.0060	0.0922	0.0064	0.0017

Table 6
The variation of accuracy, number of connected components, Euler number, and the total size of pixels via changing the threshold level of the continuous level of the continuous image output from the matched filter

Image 1: *using the first image of DRIVE*

Threshold level	Accuracy	Number of connected component	Euler no.	Total size
0.00	0.08742	1	1	3.30E + 05
0.05	0.42293	35	−89	2.19E + 05
0.10	0.43660	58	−156	2.15E + 05
0.15	0.45573	73	−327	2.09E + 05
0.20	0.48993	63	−687	1.97E + 05
0.25	0.57536	66	−926	1.70E + 05
0.30	0.71129	111	−438	1.24E + 05
0.35	0.82943	247	52	83 431
0.40	0.89221	201	126	60 583
0.45	0.92679	179	137	46 559
0.50	0.94262	116	86	38 566
0.55	0.94965	103	81	33 396
0.60	0.95274	88	68	29 610
0.65	0.95316	84	68	26 102
0.70	0.95199	89	78	22 970
0.75	0.94990	86	77	20 159
0.80	0.94800	74	69	17 942
0.85	0.94600	79	75	16 169
0.90	0.94354	65	62	14 408
0.95	0.94086	74	72	12 810
1	0.93840	64	63	11 476

The two-stage matched filter is used here with $(L_1, \sigma_1, T_1) = (10.8, 1.9, 8)$ and $(L_2, \sigma_2, T_2) = (7.6, 1.9, 8)$.

Table 7
Comparison of the accuracy using the optimum threshold found with the connected component method and that of the maximum accuracy

Image number	MA	Threshold value that gives MA	Optimum threshold using connected component	Accuracy corresponds to optimum threshold	Error rate between MA and accuracy corresponding to optimum threshold	Error rate between threshold gives MA and optimum threshold
1	0.95316	0.65	0.65	0.95316	0.0000	0.00
2	0.95503	0.70	0.75	0.95379	0.00124	0.05
3	0.95396	0.50	0.55	0.95269	0.00127	0.05
4	0.95529	0.65	0.75	0.95421	0.00108	0.10
5	0.96077	0.50	0.55	0.96010	0.00067	0.05
6	0.94901	0.55	0.65	0.94593	0.00308	0.10
7	0.94588	0.65	0.50	0.93559	0.01029	0.15
8	0.95501	0.75	0.60	0.94741	0.0076	0.15
9	0.96087	0.60	0.55	0.96083	0.00001	0.05
10	0.94865	0.80	0.65	0.94392	0.00473	0.15
11	0.95400	0.60	0.65	0.95331	0.00069	0.05
12	0.94450	0.60	0.70	0.94190	0.0026	0.10
13	0.95734	0.70	0.70	0.95734	0.0000	0.00
14	0.95026	0.75	0.75	0.95026	0.0000	0.00
15	0.95696	0.65	0.75	0.95585	0.00111	0.10
16	0.95810	0.75	0.80	0.95743	0.00067	0.05
17	0.95449	0.65	0.60	0.95368	0.00081	0.05
18	0.95422	0.50	0.45	0.95297	0.00125	0.05
19	0.94836	0.50	0.55	0.94731	0.00105	0.05
20	0.94956	0.60	0.60	0.94956	0.00000	0.00
Mean	0.95327	0.6325	0.6375	0.95136	0.00190	0.065
Standard deviation	0.00460	0.0921	0.0958	0.00627	0.00271	0.048

The two-stage matched filter is used with $(L_1, \sigma_1, T_1) = (10.8, 1.9, 8)$ and $(L_2, \sigma_2, T_2) = (7.6, 1.9, 8)$.

obtained from the above method are compared with those of the maximum accuracy for the two stage matched filter as shown in Table 7.

5. Conclusions

In this work we did improve the response and the performance of the Gaussian matched filter to be used to detect blood vessels of the digital retina by finding better filter parameters. A general purpose optimization procedure is proposed to be used to find any better operation for blood vessel detection. Though we limited the task to finding better filter parameters, it might be used to find the best threshold and hence better segmentation method. We also showed among other things that the red and the blue band response are comparable to the performance of the green band. The matched filter with the parameters found in this work is compared in performance to the best well-known methods if not better. A two stage matched filter that has two filters (two sets of filter parameters are found using the optimization procedure) outperforms the single pass matched filter method with its area under ROC curve reaching 0.95. A method to find the best threshold and hence the best segmented image is proposed; this method depends on finding the number of connected component in a set of segmented images obtained from one continuous image which is the output of the matched filter. Using this method, the average accuracy of the segmented images is 0.951 compared to the maximum average accuracy which is 0.953.

6. Summary

In this paper the matched filter response to the detection of blood vessels is increased by proposing better filter parameters. Those filter parameters are found using an optimization procedure on 20 retina images of the DRIVE database. A technique to find the best threshold value for the continuous matched filter output image and hence the best segmented vessel image is also discussed.

The matched filter has (mainly) three important parameters controlling its response, those parameters were estimated experimentally as shown in the paper [1], while in our work we use an exhaustive search optimization procedure to find the best parameters of the matched filter. Our experiments showed that the newly found filter parameters did improve the responses of the matched filter and therefore the vessel detection has been improved rigorously.

The output of matched filter is a continuous image; therefore, a thresholding procedure should be used to segment the blood vessels. The simplest method is to experimentally estimate some threshold value (by averaging the best thresholds of many images according to the maximum accuracy of vessels compared to the reference vessel hand labeled image). While the average threshold seems to work well, we propose an automated method that estimates the threshold value from one image using the number of connected component and Euler number in the thresholded image. To be more specific, the continuous matched filter output image is thresholded gradually

until the first local minima in the number of connected component occurs which we choose as the best segmented vessel image (corresponding to the best threshold). In fact, we are not in need for the best threshold in this case, but in a need for the best vessel segmented image.

It is a common practice to use the green band for vessel detection (since digital retinal images are color images); we showed that using the red band, or the blue band, vessel segmentation using the matched filter is comparable to that of the green band.

References

[1] S. Chaudhuri, S. Chatterjee, N. Katz, M. Nelson, M. Goldbaum, Detection of blood vessels in retinal images using two dimensional matched filters, IEEE Trans. Med. Imaging 8 (3) (1989) 263–269.

[2] A. Banumathi, R. Karthika, A. Kumar, Performance analysis of matched filter techniques for automated detection of blood vessels in retinal images, TENCON 2003, Conference on Convergent Technologies for Asia-Pacific Region, vol. 2, October 2003, pp. 543–546.

[3] M. Goldbaum, S. Moezzi, A. Taylor, S. Chatterjee, J. Boyd, E. Hunter, R. Jain, Automated diagnosis and image understanding with object extraction, object classification, and inferencing in retinal images, IEEE International Conference on Image Processing, Proceedings, vol. 3, September 1996, pp. 695–698.

[4] W. Hart, M. Goldbaum, B. Cote, P. Kube, M. Nelson, Automated measurement of retinal vascular tortuosity, in: Proceedings AMIA Fall Conference, 1997, pp. 459–463.

[5] C. Sinthanayothin, J.F. Boyce, T.H. Williamson, H.L. Cook, E. Mensah, S. Lal, D. Usher, Automated detection of diabetic retinopathy on digital fundus images, Diabetic Med. 19 (2) (2002) 105–112.

[6] F. Zana, J.C. Klein, Segmentation of vessel like patterns using mathematical morphology and curvature evaluation, IEEE Trans. Image Process. 10 (7) (2001) 1010–1019.

[7] J. Staal, B. Ginneken, M. Niemeijer, A. Viegever, M.D. Abramoff, Ridge based vessel segmentation in color images of the retina, IEEE Trans. Med. Imaging 23 (4) (2004) 501–509.

[8] M. Niemeijer, J. Staal, B. van Ginneken, M. Loog, M.D. Abràmoff, Comparative study of retinal vessel segmentation methods on a new publicly available database, in: Amini, A. Amir, Manduca, Armando (Eds.), Medical Imaging: Physiology, Function, and Structure from Medical Images, Proceedings of the SPIE, vol. 5370, 2004, pp. 648–656.

[9] L. Jorge, C. Roberto, J. Herbert, Blood vessels segmentation in retina: preliminary assessment of the mathematical morphology and of the wavelet transform techniques, XIV Brazilian Symposium on Computer Graphics and Image Processing, 2001.

[10] O. Chutatape, L. Zheng, S.M. Krishnan, Retinal blood vessel detection and tracking by matched Gaussian and Kalman filter, in: Proceedings 20th Annual Conference IEEE Engineering in Medicine and Biology Society, vol. 20 (6), October 1998, pp. 3144–3149.

[11] A. Hoover, V. Kouzntesova, M. Goldbaum, Locating blood vessels in retinal images by piecewise threshold probing of a matched filter responses, IEEE Trans. Med. Imaging 19 (3) (2000) 203–210.

[12] L. Gang, O. Chutatape, S.M. Krishnan, Detection and measurement of retinal vessels in fundus image using amplitude modified second order Gaussian filter, IEEE Trans. Biomed. Eng. 49 (2) (2003) 168–172.

[13] F. Zana, J.C. Klein, A multimodal registration algorithm of eye fundus images using vessels detection and Hough transform, IEEE Trans. Med. Imaging 18 (5) (1999) 419–428.

[14] N. Otsu, A threshold selection method from gray-level histograms, IEEE Trans. Syst. Man Cybernet. 9 (1979) 62–66.

[15] R.C. Gonzalez, R.E. Woods, Digital Image Processing, second ed., Prentice-Hall, New Jersey, 2002.

[16] R. Kirsch, Computer determination of the constitute structure of biomedical images, Comput. Biomed. Res. 4 (3) (1971) 315–328.

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