International Journal of Engineering & Technology, 7 (4.33) (2018) 110-113

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research paper

Retinal Fundus Image Blood Vessels Segmentation via Object-Oriented Metadata Structures

Ahmad Firdaus Ahmad Fadzil[1]*, Zaaba Ahmad[2], Noor Elaiza Abd Khalid[3], Shafaf Ibrahim[1]

[1]*Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA, Melaka Branch, Jasin Campus, Merlimau, 77300 Melaka, Malaysia*
[2]*Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA, Perak Branch, Tapah Campus, Tapah Road, 35400 Perak, Malaysia*
[3]*Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA, Shah Alam, 40450 Selangor, Malaysia*
**Corresponding author E-mail: firdausfadzil@melaka.uitm.edu.my*

Abstract

Retinal fundus image is a crucial tool for ophthalmologists to diagnose eye-related diseases. These images provide visual information of the interior layer of the retina structures such as optic disc, optic cup, blood vessels and macula that can assist ophthalmologist in determining the health of an eye. Segmentation of blood vessels in fundus images is one of the most fundamental phase in detecting diseases such as diabetic retinopathy. However, the ambiguity of the retina structures in the retinal fundus images presents a challenge for researcher to segment the blood vessels. Extensive pre-processing and training of the images is necessary for precise segmentation, which is very intricate and laborious. This paper proposes the implementation of object-oriented-based metadata (OOM) structures of each pixel in the retinal fundus images. These structures comprise of additional metadata towards the conventional red, green, and blue data for each pixel within the images. The segmentation of the blood vessels in the retinal fundus images are performed by considering these additional metadata that enunciates the location, color spaces, and neighboring pixels of each individual pixel. From the results, it is shown that accurate segmentation of retinal fundus blood vessels can be achieved by purely employing straightforward thresholding method via the OOM structures without extensive pre-processing image processing technique or data training.

Keywords: *retinal fundus image; blood vessels; object-oriented structures; metadata; image segmentation*

1. Introduction

Visual information in retinal fundus image provide a crucial tool for ophthalmologists to diagnose eye-related diseases. Pathological features of retinal fundus images such as optic disc, optic cup, blood vessels, and macula [9] are essential towards diagnosing eye-related diseases. Diabetic retinopathy [12-13, 17], an eye disease touted as one of the leading cause of blindness is one of the diagnosis that can be accomplished via segmenting the blood vessels of the retinal fundus image.

However, the ambiguity of the retinal fundus images presents a challenge for researcher to accurately segment the blood vessels in the image. The appearance of the blood vessels in terms of color intensity diverges from different region of the images. Hence, most researches emphasize on the either the extensive pre-processing of the images [10, 12, 15] or the massive learning datasets of the images [4-7, 19]. This resulted in the methods requires intricate and laborious processing.

This paper proposes an implementation of object-oriented metadata (OOM) structures that provides additional description of each pixel within an image. Additional information regarding a pixel such as the location, neighboring pixels, and alternate color spaces can be utilized as a tool to determine which pixels belong to different pathological features in a retinal fundus images. Therefore, instead of relying on intensive preprocessing image processing operation and massive training datasets, this approach relies on the metadata of each pixel to produce an accurate segmentation.

2. Related Works

2.1. Image Pre-processing

Segmentation of blood vessels in retinal fundus images conventionally employs extensive image pre-processing to enhance the original images. This is done to increase the visibility of the pathological features in retinal fundus images to allow more precise segmentation. The ambiguous appearance of the blood vessels [15] in the retinal fundus image necessitate different enhancement towards the original image. Despite the blood vessels features can be perceived via the human eye, the level of color intensity of red, green, and blue channel that describe the blood vessels features may also describe the background of the retinal fundus image.

Examples of image pre-processing techniques applied to segment blood vessels in retinal fundus image includes low and high pass filtering [18] to sharpen or smoothen the image, histogram equalization to adjust the contrast of the image and Gaussian filtering for noise elimination [19] are some of the image preprocessing that has been employed before the segmenting the blood vessels in retinal fundus image.

These preprocessing requires intricate processing with each filters or enhancement may take even more time then the segmentation process itself. It can also be contended that different type of images may require different types of image preprocessing, hence making the process not robust enough for critical process such as segmentation of blood vessels in retinal fundus image.

2.2. Machine Learning

Recent trends in image processing algorithm shows the advent of machine learning algorithm as the de-facto standard for providing accurate image segmentation. Numerous researches have employed machine learning of different types and methods to segment blood vessels in retinal fundus images. Machine learning methods such as artificial neural network (ANN) [3, 8], support vector machine (SVM) [14], and recently convolutional neural network (CNN) [7, 19] has shown to be a reliable method to provide an accurate segmentation towards the blood vessels in retinal fundus images.
Nevertheless, employing machine learning requires massive amount of training datasets to allow the algorithm to learn different pathological features in the retinal fundus images. This learning process can be very laborious depending on the size of the training datasets and the number of layers employed in the learning structures.
The number of training datasets can be amounting from hundreds to thousands [5, 19] of data as increase in terms of the number of training data will allow the algorithm to produce more accurate results. Unless adequate learning datasets and layers employed, the machine learning algorithm will unable to accurately segment the blood vessels in retinal fundus images.

3. Methodology

This paper proposes the employment of object-oriented metadata (OOM) structures for describing each individual pixel within the retinal fundus images. Object-oriented programming (OOP) is a method employed in computer science that can describe an entity as an "object". OOP has become a ubiquitous method in programming different type of applications as its ability to encapsulate the data belonging to an object allow different types of processing to be executed on the object [16, 20]. In this paper, the employment of OOP to provide an OOM for individual pixels in the retinal fundus images will be discussed. The process that accompanies the OOM structures will also be deliberated on how OOM can contribute to accurate segmentation of blood vessels in retinal fundus images.
There are four phases that have been instigated in producing this paper. The phases are data collection, object-oriented metadata structures design, image segmentation algorithm design, and finally testing and evaluation.

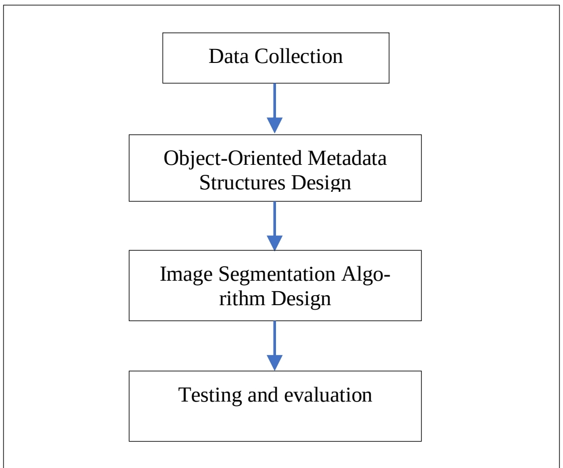


Fig. 1: Methodology Phases Flow

Figure 1 illustrates the phases of methodology in this paper. Each subsequent subtopic will further deliberate each phase in details.

3.1. Data Collection

The data collection phase gathers retinal fundus image datasets from internet sources. Varieties of different internet sources can be visited for complete retinal fundus image datasets complete with ground truth data (manual annotation) [1, 11, 19]. In this paper, DRIVE retinal fundus dataset [11] is preferred as the data to be used in this research. This is due to its high-quality retinal fundus image and its specific ground truth data emphasizes on the segmentation of the blood vessels.

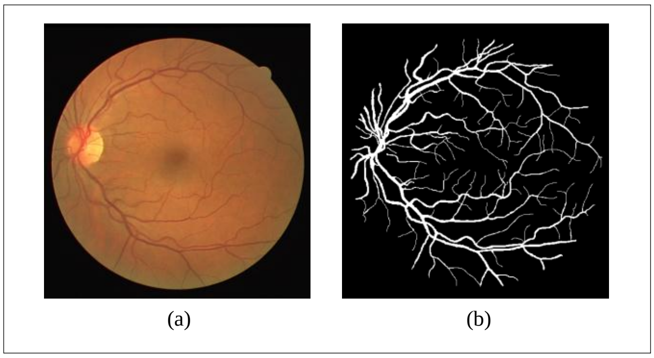


Fig. 2: Sample DRIVE Retinal Fundus Image Data

Figure 2 illustrates examples of DRIVE retinal fundus image dataset, with the figure in (a) represents the original image while the image in figure (b) is the corresponding ground truth (manually annotated blood vessels segmentation). There are 20 training and 20 test data available in the dataset. The amount of data is considerably smaller than other available dataset. Though, this complements the dispute of this paper whereas the algorithm ought to be able to accurately segment the data without the necessity to train the algorithm as most research that employ machine learning algorithm advocates.

3.2. Object-Oriented Metadata (OOM) Structures Design

In this phase, the design process of the OOM structures to describe the retinal fundus image is reflected. The OOM structures is designed to augment additional information regarding each pixel within the retinal fundus image. Conventional algorithm usually treats the image data as simply a collection of pixels in the form of red, green, and blue color intensity value. These combinations in the end will decide the appearance of the pixel within the image.
It can be contended however, each pixel in the image can be described with more detailed information.

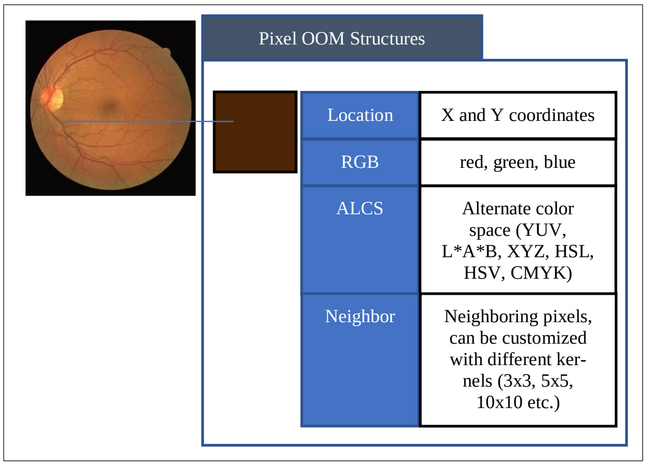


Fig. 3: Pixel's Object-Oriented Metadata (OOM) Structures

Figure 3 explicates the OOM structures that can be accommodated to each individual pixel. Instead of storing each pixel purely with its RGB intensity values, they can be described with more information such as location, color spaces, and neighboring pixels. This description creates a new set of metadata that can accommodate different valuable information regarding each individual pixel that can be utilized for segmentation purposes. For example, different information on color spaces allow each pixel to behave differently according to respective color spaces. HSL color spaces for example, provide the hue, saturation, and luminosity of the pixel compared to the red, green, and blue intensity by conventional RGB color spaces. These different criteria allow different thresholding values to be incorporated for more accurate segmentation.

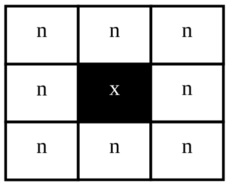


Fig. 4: 3x3 Pixel's Neighbors

Pointers to neighbouring pixels will also be accommodated to allow interaction between different pixels. Neighbouring pixels are crucial especially when connectivity of each pixels is being considered. This OOM structures is designed to accommodate crucial information that can be utilized for segmentation of blood vessels in retinal fundus images.

3.3. Image Segmentation Algorithm Design

Manipulating image data using the OOM structures is more flexible when being compared with conventional RGB bitmap data. This structure allow independent processing of each pixel as every pixel is accommodated with crucial information that can be utilized for image segmentation. Therefore, before segmentation process is executed, the algorithm will first convert the bitmap data into OOM structures.

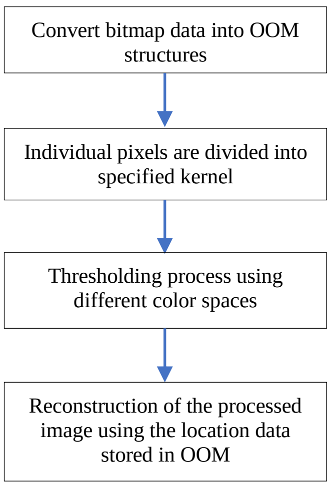


Fig. 5: Segmentation Algorithm Flow

After conversion, the segmentation process will begin where different thresholding values are applied towards six different color spaces in the OOM structures. The thresholding value utilized in this research are calculated based on the basic statistical operation such as average, median, max, and min. This is done since the blood vessels while ambiguous in terms of its color intensity, can be visibly conceived via human eyes. Therefore, employing basic statistical operation mentioned earlier hypothetically can distinguish the blood vessels features from other features such as background, optic disc, optic cup, and macula. This technique is touted as "adaptive thresholding" where the thresholding value will on be applied to corresponding kernel in the OOM.

The neighbouring pixels stored in different kernel size of 3x3, 5x5, 10x10, and 15x15 according to suitability of the image. Images with more ambiguous color will employ smaller kernel size to avoid uneven thresholding. It is also worth noting that employing larger kernel may create the "square effect" where the end results appear in the form of squares across the segmented image. This can be eliminated during the reconstruction process of the final segmented image by considering the connectivity of one kernel towards the next.

Without essential information provided by the OOM structures, the segmentation and reconstruction process cannot be achieved as employing the conventional bitmap image data only provide the RGB intensity value of each pixel. Providing each pixel with additional metadata enables more comprehensive processing without the intensive pre-processing of image or extensive learning process via machine learning algorithms.

3.4. Testing and Evaluation

In this paper, the algorithm proposed are tested using receiver operating characteristics (ROC) [5, 19], where the sensitivity and specificity of each results are recorded to determine whether the algorithm performs according to the theory proposed.

$$\textit{Sensitivity (true positive rate)} = \frac{\textit{true positive}}{\textit{true positive} + \textit{false negative}} \quad (1)$$

$$\textit{Specificity (true negative rate)} = \frac{\textit{true negative}}{\textit{true negative} + \textit{false positive}} \quad (2)$$

In (1) and (2) explicates the calculation utilized to determine the accuracy of the segmented blood vessels images. True positive is the case where the segmented region complements the manually annotated blood vessels done by experts. The true negative otherwise denotes the case where the non-segmented region complements the experts' non-segmented region. The false positive and false negative are the reverse of the earlier whereas the segmented and non-segmented results does not correspond with the experts' manual annotated results.

The sensitivity (true positive rate) suggests how sensitive is the algorithm in determining the correct features for segmentation. In this case, this calculation presents how well the algorithm proposed able to accurately segment the blood vessels features of retinal fundus images. On the other hand, the specificity (true negative rate) states how well the algorithm can distinguish unrelated results from the desired segmentation. In this case, this calculation describes how the algorithm can assimilate other features other than blood vessels in the retinal fundus images. In the next section, the results of blood vessels retinal fundus image segmentation via OOM structures will be further deliberated.

4. Results and Discussion

The results are obtained by overlaying the segmented images with the ground truth image, obtaining the count of overlapped pixels in both images. The proposed algorithm is tested using 40 DRIVE retinal fundus image dataset.

Each execution of the algorithm utilizes similar thresholding operation stated in previous section. However, the size of neighboring pixels or the kernel are adjusted according to the appearance of the retinal fundus images. Brighter images with ambiguous color utilize smaller kernel values while clearer images with even color utilizes larger kernel values to optimize each cases' segmentation.

Table 1: Sample Blood Vessels Segmentation Results

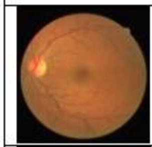
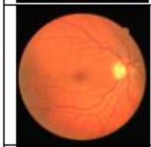
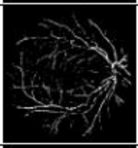
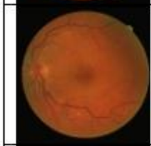
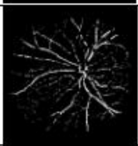
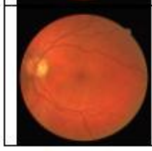
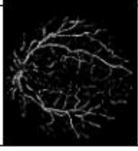
Original	Ground Truth	Segment	Results Sensitivity (Sn) Specificity (Sp)
			Sn = 0.86 Sp = 0.93
			Sn = 0.84 Sp = 0.95
			Sn = 0.85 Sp = 0.90
			Sn = 0.80 Sp = 0.91
			Sn = 0.76 Sp = 0.89

Table 1 depicts example of 5 segmentation results from the 40 images employed. The result in terms of sensitivity is considerably lower than specificity. The maximum value of specificity for the overall image tested peaks consistently at more than 0.9 while the maximum sensitivity value can only reach maximum of less than 0.9. This result suggest that the algorithm manages to distinguish background from the intended segmentation features.

However, there are still plenty amount of blood vessels features that are missed by the segmentation as illustrated by the result with minimum sensitivity number of less than 0.8. While employing OOM structures such as neighboring pixels and alternate color spaces proves to allow accurate segmentation of the blood vessels features in retinal fundus image, this result suggest there are plenty of room for the algorithm to be improved.

5. Conclusion

From the results gathered, it can be verified that OOM structures provide a robust tool for segmentation of blood vessels in retinal fundus images by purely employing straightforward thresholding operation. This is accomplished without prior extensive image pre-processing and any machine learning training procedure. Nevertheless, the OOM can be further improved especially in terms of its sensitivity of the segmentation. While it shows that the approach manages to successfully distinguishes the features intended for segmentation than the background, its value in terms of sensitivity leaves additional room for improvement. The potential of employing OOM however persist as a very stimulating approach as these metadata can also be further optimized techniques such via evolutionary computing for example. These metadata can also be executed with machine learning approach to provide an even more powerful segmentation approach.

References

[1] Carmona, E. J., Rincón, M., García-Feijoó, J., & Martínez-de-la-Casa, J. M. (2008), Identification of the optic nerve head with genetic algorithms. *Artificial Intelligence in Medicine* 43(3), 243-259.

[2] Decencière, E., Cazuguel, G., Zhang, X., Thibault, G., Klein, J. C., Meyer, F., Marcotegui, B., Quellec, G., Lamard, M., Danno, R., & Elie, D. (2013), TeleOphta: Machine learning and image processing methods for teleophthalmology. *IRBM 34*(2), 196-203.

[3] Franklin, S. W., & Rajan, S. E. (2014), Retinal vessel segmentation employing ANN technique by Gabor and moment invariants-based features. *Applied Soft Computing 22*, 94-100.

[4] Fu, H., Xu, Y., Lin, S., Wong, D. W. K., & Liu, J. (2016), Deepvessel: Retinal vessel segmentation via deep learning and conditional random field. *Proceedings of the International Conference on Medical Image Computing and Computer-Assisted Intervention*, pp. 132-139.

[5] Gulshan, V., Peng, L., Coram, M., Stumpe, M. C., Wu, D., Narayanaswamy, A., ... & Kim, R. (2016), Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. Journal of the American Medical Association *316*(22), 2402-2410.

[6] Li, Q., Feng, B., Xie, L., Liang, P., Zhang, H., & Wang, T. (2016), A cross-modality learning approach for vessel segmentation in retinal images. *IEEE Transactions on Medical Imaging 35*(1), 109-118.

[7] Maji, D., Santara, A., Mitra, P., & Sheet, D. (2016), Ensemble of deep convolutional neural networks for learning to detect retinal vessels in fundus images. https://arxiv.org/pdf/1603.04833.pdf.

[8] Mann, K. S., & Kaur, S. (2017), Segmentation of retinal blood vessels using artificial neural networks for early detection of diabetic retinopathy. *AIP Conference Proceedings* 1836(1), 1-9.

[9] Miri, M. S., Abràmoff, M. D., Lee, K., Niemeijer, M., Wang, J. K., Kwon, Y. H., & Garvin, M. K. (2015), Multimodal segmentation of optic disc and cup from SD-OCT and color fundus photographs using a machine-learning graph-based approach. *IEEE Transactions on Medical Imaging* 34(9), 1854-1866.

[10] Mittal, D., & Kumari, K. (2015), Automated detection and segmentation of drusen in retinal fundus images. *Computers and Electrical Engineering* 47, 82-95.

[11] Niemeijer, M., Staal, J., van Ginneken, B., Loog, M., & Abramoff, M. D. (2004), Comparative study of retinal vessel segmentation methods on a new publicly available database. *Medical Imaging: Image Processing* 5370, 648-657.

[12] Orlando, J. I., Fracchia, M., del Río, V., & del Fresno, M. (2017), Retinal blood vessel segmentation in high resolution fundus photographs using automated feature parameter estimation. *Proceedings of the 13th International Conference on Medical Information Processing and Analysis*, pp. 1-13.

[13] Pal, A. L., Prabhu, S., & Sampathila, N. (2015), Extraction of retinal blood vessels from retinal fundus image for computer aided diagnosis. *Proceedings of the National Joint Conference on Innovations in Engineering and Technology, pp.* 400-403.

[14] Princye, P. H., & Vijayakumari, V. (2018), Retinal disease diagnosis by morphological feature extraction and SVM classification of retinal blood vessels. *Biomedical Research*, 2017, 22-30.

[15] Roychowdhury, S., Koozekanani, D. D., & Parhi, K. K. (2015), Blood vessel segmentation of fundus images by major vessel extraction and subimage classification. *IEEE Journal of Biomedical and Health Informatics* 19(3), 1118-1128.

[16] Salazar-Gonzalez, A., Kaba, D., Li, Y., & Liu, X. (2014), Segmentation of the blood vessels and optic disk in retinal images. *IEEE Journal of Biomedical and Health Informatics* 18(6), 1874-1886.

[17] Smith, B. (2015), Object-oriented programming. In AdvancED ActionScript 3.0: Design Patterns. California: Apress, pp. 1-23.

[18] Solkar, S. D., & Das, L. (2017), Survey on retinal blood vessels segmentation techniques for detection of diabetic retinopathy. *International Journal of Electronics, Electrical and Computational 6(6), 490-496*.

[19] Wang, S., Yin, Y., Cao, G., Wei, B., Zheng, Y., & Yang, G. (2015), Hierarchical retinal blood vessel segmentation based on feature and ensemble learning. *Neurocomputing* 149, 708-717.

[20] Xie, T., Marinov, D., Schulte, W., & Notkin, D. (2005), Symstra: A framework for generating object-oriented unit tests using symbolic execution. *Proceedings of the International Conference on Tools and Algorithms for the Construction and Analysis of Systems*, pp. 365-381.