Hybrid of the PMD Filter, the K-Means Clustering Method and the Level Set Method for Exudates Segmentation

Syaiful Anam, Zuraidah Fitriah and Nur Shofianah
Mathematics Department, Brawijaya University, Veteran Street, Malang, Indonesia

Keywords: Diabetic Retinopathy, Exudates, Segmentation, Level Set Method, PMD Filter, K-Means Method.

Abstract: Diabetic retinopathy is an eye disease caused by diabetes mellitus. Early diagnosis of diabetic retinopathy is necessary to avoid blindness. Exudate is one of the symptoms of the diabetic retinopathy. Ophthalmologists use the fundus images of a patient to extract the exudates for evaluating the diabetic retinopathy. The exudates segmentation of the fundus images is a difficult task for ophthalmologists because the fundus images often have poor qualities, such as the boundaries between objects in a less clear, low contrast and containing noise. There are many methods of segmentation, one of which is by using an active contour model. One of the known active contour models is the level set method. It has been widely applied in many applications in the image processing. However, it cannot work well on the noisy image. This paper proposes the hybrid of the PMD filter, K-means clustering method and the level set method for segmenting exudates. The PMD filter and K-means method are exploited to remove the noise. From the results of the experimental results obtained that the hybrid of K-means clustering method and the level set method is able to work better in segmenting fundus images than the standard level set method.

1 INTRODUCTION

The prevalence of diabetes mellitus has become more rapidly in the middle income and low-income countries. The number of people which have diabetes mellitus significantly increased (Weng and Hu, 2017). Diabetes is one of the metabolic diseases that occur by increasing a blood sugar level in the body. The increment of blood sugar level in the body may occur when the body has a problem in insulin secretion or make use of the formed insulin. According to the World Health Organization, diabetes mellitus is a disease which is characterized by increasing a blood sugar level. It is accompanied by metabolic disorders of carbohydrates, lipids, and proteins. Diabetes mellitus may cause many complication diseases, for example, vascular complication. Classically the diabetes mellitus vascular complication diseases are categorized into two which are microvascular and macrovascular. The most common diabetes mellitus microvascular complication is diabetic retinopathy.

Diabetic retinopathy is a damage to the retinal microvascular system due to prolonged hyperglycemia. It may lead to blindness. Nowadays in the western word, the diabetic retinopathy causes the blindness in the working people (Semeraro et al., 2015). Diabetic retinopathy is characterized by a narrowing of retinal vessels. It is caused by the accumulation of fluids and fatty material in the retina. It causes bleeding in the retinal vessel so that it leads to blurred vision. If this condition is left, then it can cause severe vision damage as well as blindness. The risk of diabetic retinopathy can be prevented by detecting and controlling blood sugar, blood pressure and lipids appropriately (Tarr et al., 2013).

Ophthalmologists use the retinal images known as the fundus image is to diagnose diabetic retinopathy. From fundus, it can be seen the small blood vessels, microaneurysm, and exudate, however, it may be in low contrast. For diagnosis the diabetic retinopathy, ophthalmologists usually use the fundus image by evaluating the exudate which is one of the symptoms of diabetic retinopathy. Therefore, the extraction of the exudate on the fundus image is needed (Madhukar et al., 2017). The exudate extraction of the fundus image is a difficult task for ophthalmologists because the fundus image often has poor qualities. Therefore, a method that automatically aided computers will help an

Anam, S., Fitriah, Z. and Shofianah, N.
Hybrid of the PMD Filter, the K-Means Clustering Method and the Level Set Method for Exudates Segmentation.
DOI: 10.5220/0008517901080116
In *Proceedings of the International Conference on Mathematics and Islam (ICMIs 2018)*, pages 108-116
ISBN: 978-989-758-407-7

ophthalmologist to recognize and extract the signs of diabetic retinopathy disease.

Segmentation method is one of the methods which can be used for extracting the exudate. The image segmentation method will divide the image into a separate set of regions with uniform texture attributes, etc. (Dhivya and Anitha, 2014). It can be applied for segmenting the fundus image area into two parts i.e. the exudate and other areas. Many image segmentation methods have been proposed. The image segmentation method can be divided into two categories, i.e. edge based method and the area-based method (Airouche et al., 2014). The level set method has been proposed for image segmentation. It is developed by using variational models and partial differential equations. This method has been widely used successfully for segmenting the medical images (Anam et al., 2013, Anam et al., 2014a, 2014b). The level set method has some advantages over the other methods, i.e. the snake method thresholding method and region growing method. However, it cannot work well when the images contain noise. The level set contour will stop prematurely in the evolution process and it results in unsatisfactory segmentation when it is applied for the noisy image. Many representative conventional noise reduction methods have been proposed, i.e. the median filters (Russ, 2006), morphology analysis (Soille, 1999), bilateral filters (Tomasi and Manduchi, 1998). However, if they are applied for fundus image, the exudate boundaries also become dull unexpectedly. Above all those methods, Perona-Malik Diffusion (PMD) filter is able to preserve an edge effectively in the image smoothing. If the PMD filter is applied to a fundus image, the exudate boundaries can be preserved, but several noises cannot be removed. K-means is a clustering method which has been successfully applied for an de image noise reduction or an image denoising (Barca and Rumantir, 2008, Pandey and Bhadauria, 2016). Barca and Rumantir have proposed a modified K-means method. It is able to eliminate the noise in the multicolored motion capture image sequences. While Pandey and Bhadauria have proposed the method for removing the high-density impulse noise in the image by using a modified k-mean algorithm. For this reason, this research uses the level set with the PMD filter and the K-means method. The PMD filter and the K-means method are used as preprocessing to avoid the stopping premature of evolution curve in the level set. For this reason, the level set, the PMD filter and K-means methods for image segmentation will be considered in this paper.

This paper proposes a hybrid of the PMD filter, the K-means clustering method and the level set method for segmenting exudate in fundus images. The results of the exudate segmentation in the fundus image will give the information of diabetic retinopathy sign for ophthalmologists.

2 RELATED WORKS

This section will discuss several theories and the previous research which is related to this research, such as diabetic retinopathy and fundus image, image segmentation, Perona-Malik diffusion filter, K-Means, and level set method.

2.1 Diabetic Retinopathy and Fundus Image

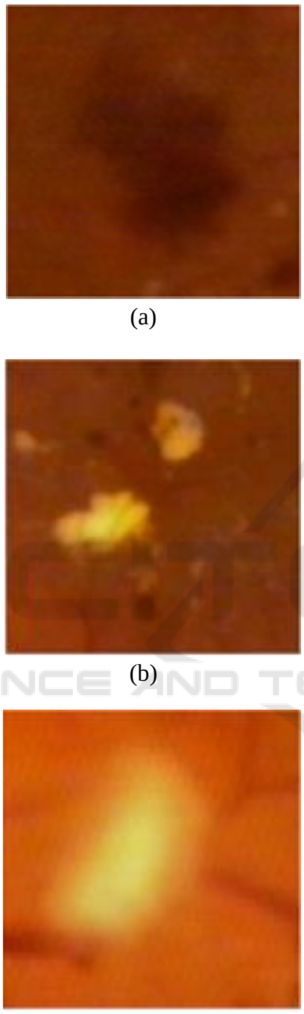
Diabetes mellitus is a chronic disease which is caused by an obtained deficiency in the insulin production, or by the ineffective insulin production. Diabetic retinopathy is a microvascular complication caused by diabetes mellitus. If it is not treated, it causes blindness.

The first symptom of the diabetic retinopathy appears microaneurysm. If microaneurysm is broken, it can cause hemorrhage to be seen in Figure 1(a). After that, it seems hard exudate as shown in Figure 1(b). Hard exudate is a leaky lipid formation of weakened blood vessels. Along with the severity of retinopathy disease, the blood vessels may become inhibited causing microinfarct in the retina called soft exudate as shown in Figure 1(c). The diagnosis of diabetic retinopathy using a fundus image is necessary because the disease is progressive, the example of the fundus image can be seen in Figure 2 (Anam et al., 2014b).

2.2 Segmentation

Information technology is a very rapid development in many fields, such as medical. Science and technology in image processing and artificial intelligence become a promising tool in medical technology. A level set method has been used for many applications in image segmentation, such as in detecting the bone boundaries of the hand radiography. The bone boundaries are a necessity for segmenting the bone and other areas (Anam et al.

2013). A combination of PSO and fuzzy inference has been proposed for extracting the coronary plaque boundaries in the Intravascular Ultrasound (IVUS) image. The plaque boundaries in the IVUS image are needed to be extracted for calculating the plaque area (Anam et al., 2014a). Boundary extraction of an image is one of the image segmentation methods.



(a)

(b)

(c)

Figure 1: The abnormal sign on the fundus image caused by diabetic retinopathy. (a) Hemorrhage, (b) Hard exudate, (c) Soft exudate.

Image segmentation is one of the image preprocessing methods in the image recognition and analysis task. Image segmentation divides an image into homogeneous areas based on the criteria of specific similarities of the gray level pixel. There are many conventional image segmentation methods which have been proposed, such as the gradient-based methods (Sobel method, Prewitt method, Canny method and Laplacian method) and template-based methods. Canny method cannot result in smooth segmentation (Mazid, 2013). While, the snake method cannot separate object well when the image has object more than one objects (Li et al., 2005).

Figure 2: Fundus image.

The level set method (Osher and Sethian, 1988) has been applied for image segmentation to overcome the weakness of the conventional image segmentation method. It is one of the known methods. It is very robust and accurate image segmentation method. The level set method also has been broadly used in many fields, in particular for the image segmentation (Anam et al., 2013, Anam et al., 2014a).

2.3 Anisotropic Diffusion Filter

An anisotropic diffusion filter has been developed by Perona and Malik. It is used to eliminate noise in the image and maintain the edges of an image. The Perona-Malik (PMD) filter idea is to smooth the image $u(x,y,t)$ from an original image $u_0(x,y)$ where t is diffusion parameter.

The PMD filter equation is defined by (1).

$$\begin{aligned} I_t = \frac{\partial I}{\partial t} &= div(c(x,y,t)\nabla I) \\ &= c(x,y,t)\Delta I + \nabla c(x,y,t)\nabla I, \end{aligned} \tag{1}$$

where

$$c(x,y,t) = g(\|\nabla I(x,y,t)\|) \tag{2}$$

is a coefficient of diffusion process, $\|\nabla I\|$ defines the norm of image gradient, while $g(\cdot)$ is an edge stopping function of level set which is represented by (3).

$$g(\nabla I) = \frac{1}{1+\left(\frac{\nabla I}{K}\right)^2}, \tag{3}$$

K is a diffusion strength parameter. This parameter is used for controlling the diffusion strength, $g(\cdot)$ has high values at the areas where the values of gradients are low, while it has low values at the area where the values of gradients are large.

The initial value of $I(x, y, 0)$ is given (4).

$$I(x, y, 0) = I_0(x, y). \tag{4}$$

The PMD filter in the discrete version is defined by (5).

$$I_s^{(n+1)} = I_s^{(n)} + \frac{\lambda}{|\varphi_s|}\sum g(\nabla I_{s,p}^{(n)}) I_{s,p}^{(n)}, \tag{5}$$

$s(x, y)$ is the pixel coordinates of concern, p is the neighbour pixels of $s(x, y)$. $I_s^{(n)}$ represents the pixel intensity of s when the iteration count is n. ϕ_s is the eight pixels of the neighbour of s in the North diffusion direction, North-West diffusion direction, West diffusion direction, West-South diffusion direction, South diffusion direction, South-East diffusion direction, East diffusion direction and East-North diffusion direction. $|\phi_s|$ is a pixel number of the neighbour of s, while λ represents a parameter (Perona and Malik, 1990).

2.4 K-Means Clustering Algorithm

Cluster analysis is the task which partitions a set of objects into subsets so that the objects properties in the one cluster have the high degree similarity. Clustering is an unsupervised learning method commonly used in a variety of application. It has been applied for many applications, such as image processing, machine learning, data mining, and bioinformatics.

K-means clustering algorithm is one of the popular clustering methods. It is a clustering method based on an iterative approach. The K-means clustering method divides the dataset into k groups (Santhi et al., 2011). The algorithm of K-Means clustering is can be seen in Algorithm 1.

Algorithm 1: K-means Algorithm

1. Input the data set which will be clustered and determine the number of clusters K.
2. Initialize the member of each cluster.
3. Repeat
   a. Calculate the cluster center of each cluster. It is calculated by the means of data in each cluster.
   b. K-means assigns each data in the dataset to only one of the clusters based on the nearest distance from data to each cluster centers.
4. Until no change the member of each cluster.

2.5. Level Set Method

Level set method was proposed by Osher and Sethianin (1988). It has been successfully used for many applications. The level set method has been applied for boundary detection in the medical image. The contour of the level set is defined by using the zero-level set which is called by a level set function. The contour of level set expresses the motion of the contour based on the level set function evolution. The evolution of level set curve of a parametric contour $C(x(s,t), y(s,t))$, is represented by equation (6).

$$\partial C / \partial t = FN, \tag{6}$$

t is a set points of time, while s is a parameter of evolution curve. N defines the normal vector to the curve C. F is a curve evolution speed function which will control the motion of the level set contour. The evolution of curve of (6) can be changed into a formulation of the level set. Changes made through the embedding of the dynamic contour C as the zero-level set. This paper assumes that the value of level set function ϕ is positive outside the zero-level set contour, vice versa it takes negative value inside the zero-level set contour. The inward normal vector is represented by (7), where ∇

$$N = -\nabla\varphi / |\nabla\varphi| \tag{7}$$

is a gradient operator.

By using (6) and (7), the evolution of curve of the level set in (6) is changed to (8),

$$\partial\varphi / \partial t = F|\nabla\varphi|, \tag{8}$$

which refers to as equation of a level set evolution. The formulation of the level set $\phi(x)$ used in this paper is formulated by (9).

$$\partial\phi/\partial t = \mu div(d_p(|\nabla\phi|)\nabla\phi) + \lambda\delta_\varepsilon(\phi)div(g\nabla\phi/|\nabla\phi|) + \alpha g\delta_\varepsilon(\phi), \quad (9)$$

δ_ε is a dirac delta function, div represents a divergence operator, and g defines an edge stopping function given by(10).

$$g = 1/(1+|\nabla(G_\sigma * I|), \quad (10)$$

G_σ represents the Gaussian filter, while I is an image which is to be processed (Li et al.,2010).

3 PROPOSED METHOD

This paper proposes an image segmentation method for extracting the exudate on fundus image by the hybrid of the K- means and level set methods. The data used in this research is the fundus images as shown in Figure 4. They are taken from the website http://www.it.lut.fi/project/imageret/diaretdb1/. The data are used to evaluate the proposed method. The flowchart of the proposed method is shown in Figure 3. The proposed method has several steps. First, the fundus image is inputted. Furthermore, the image in the RGB (Red, Green, Blue) color space is converted to the CIE L*a*b color space. Image in CIE L * a * b color space has 3 components which are the L (Luminance), a (reddish-greenish) and b (yellowish-bluish) components. From Figure 5, it can be seen that the reddish-greenish component is better than the yellowish-bluish and luminance components of the format CIE L*a*b for representing the exudate areas and other areas, therefore the reddish-greenish component is used for the next step.

Since the reddish-greenish component has low contrast as shown in Figure 6 (a), the contrast enhancement is necessary to be done. After the image contrast enhancement, the image is better to visual the exudate, it can be seen in Figure 6. However, the noise in the image also increases. For this reason, the noise in the image should be reduced.

This proposed method uses the PMD filter and the K-mean algorithm to reduce the noise. Firstly, the formulation of the PMD filter in the equation (5) is used for reducing the noise. The initial condition of the PMD filter in the equation (4) uses the reddish-greenish component of the image after applying the image contrast enhancement. The image result after applying the PMD filter can be seen in Figure 7. The PMD filter significantly reduces the noise. However, some noises still exist. For this reason, the K-means algorithm in Algorithm 1 is used to remove the noise. After applying the K-means algorithm, the noise disappears, and the image becomes smooth as shown in Figure 8 (b).

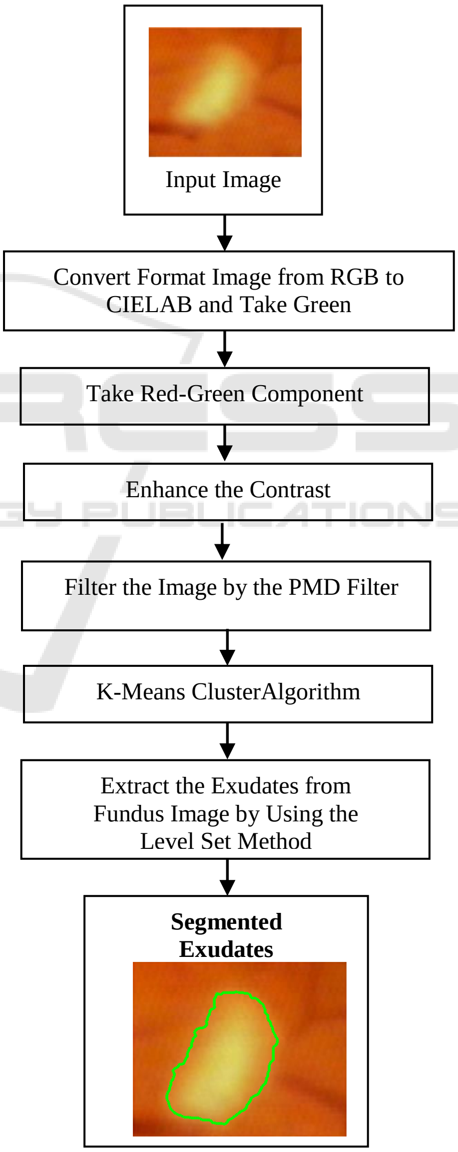


Figure 3: Flowchart of the proposed method.

The last step of the proposed method is that the image resulted by the K-means method is used as input for the level set method. The equation of the level set as shown in equation (9) is used to extract the exudate areas in the fundus image. The final result of this method can be shown in Figure 8(b). The exudate areas are the areas inside the green curve and the other areas are the areas outside the green curve.

4 RESULTS AND DISSCUSSIONS

For evaluating the proposed method performance, we use the four various test images of the fundus with the exudates as shown in Figure 4. The test images used have different colors, brightness levels, and contrast levels, this is intended to evaluate the robustness of the developed method. The test images also have different levels of clearness on the object boundaries. The image of Figure 4 (a) has the unclear object boundaries, while the level brightness of image of Figure 4 (c) is darker if it is compared to the other test images. For evaluating the performance of the proposed method, it is compared to the standard level set. The different of the standar level set and the proposed method is in the calculation of edge stopping function. The standard level uses the gaussian filter to reduce the noise, while the proposed method uses the PMD filter and K-means method.

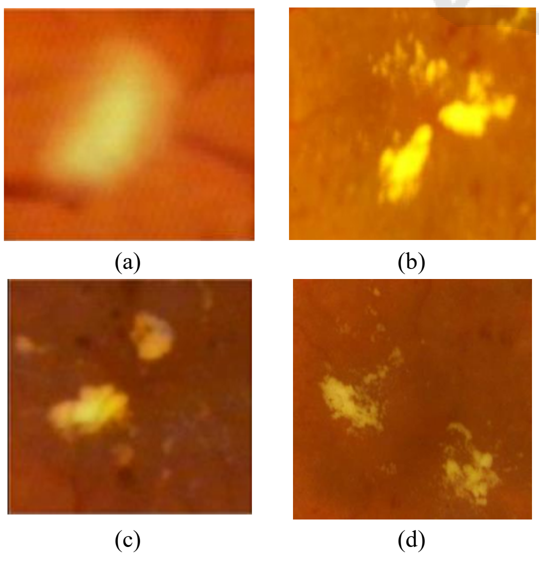


Figure 4: Fundus image data set used for evaluating the proposed method: (a) Image 1st, (b) Image 2nd, (c) Image 3th, (d) Image 4th.

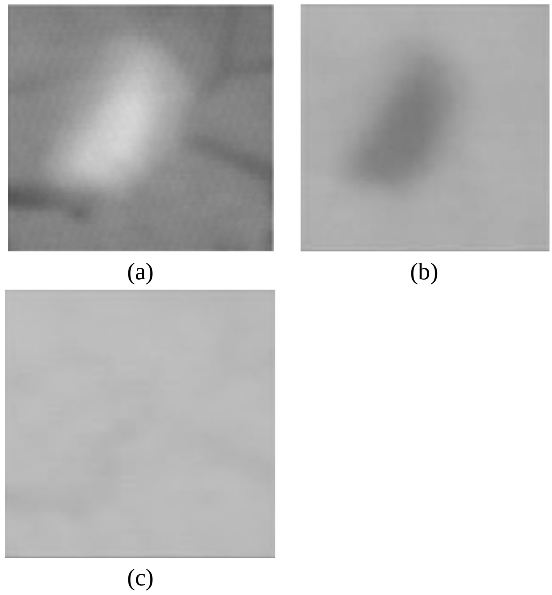


Figure 5: Component of CIE L*a*b image, (a) Reddish-greenish component, (b) Yellowish-bluish, (c) Luminance.

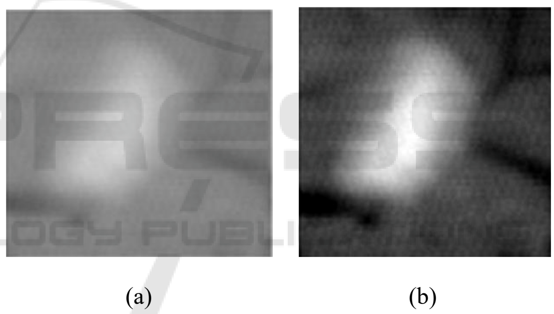


Figure 6: (a) The image before the contrast enhancement. (b) The image after the contrast enhancement.

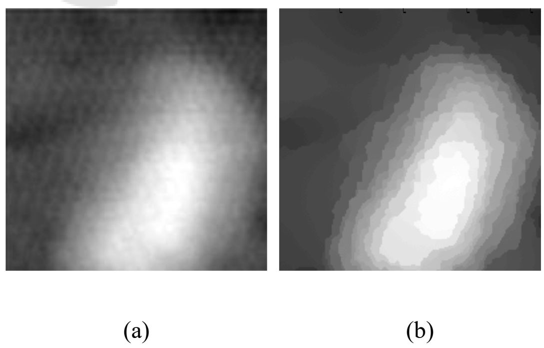
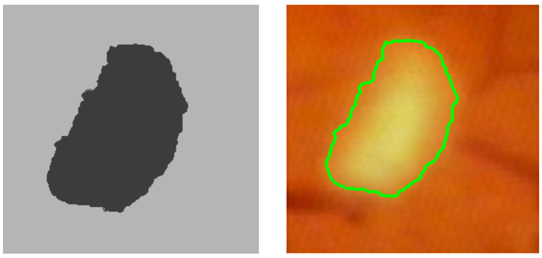
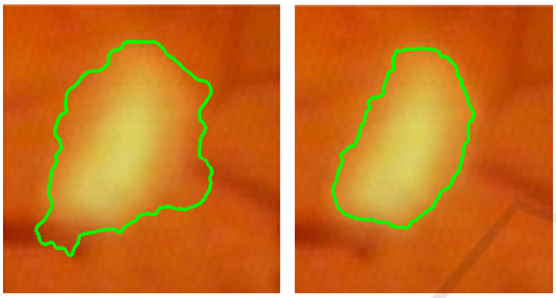


Figure 7: (a) The image before applying the PMD filter. (b) The image after applying the PMD filter.



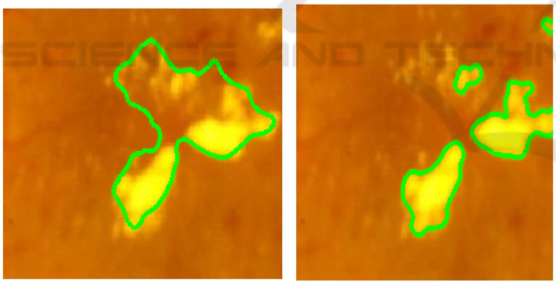
(a) (b)

Figure 8: (a) The images which is resulted by the K-means algorithm. (b) The images which is segmented by the level set algorithm.



(a) (b)

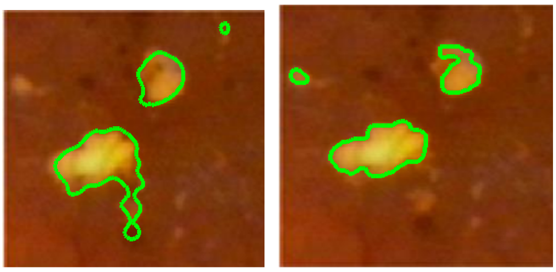
Figure 9: Exudates extraction results for image 1st. (a) Exudates extraction results by the standard level set method. (b) Exudates extraction results by the hybrid of the K-means and level set methods.



(a) (b)

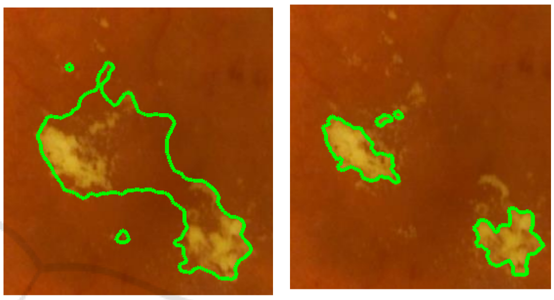
Figure 10:. Exudates extraction results for image 2nd. (a) Exudates extraction results by the standard level set method. (b) Exudates extraction results by the hybrid of the K-means and level set methods.

The images of Figure 9 (a), Figure 10 (a), Figure 11 (a) and Figure 12 (a) show the segmentation results by using the standard level set, while the images of Figure 9 (b), Figure 10 (b), Figure 11 (c) and Figure 12 (d) show the segmentation results by the hybrid of the PMD filter, the K-means and level set methods (proposed method). The proposed method is more successfully separates between the exudate areas and other areas for almost all images if it is compared to



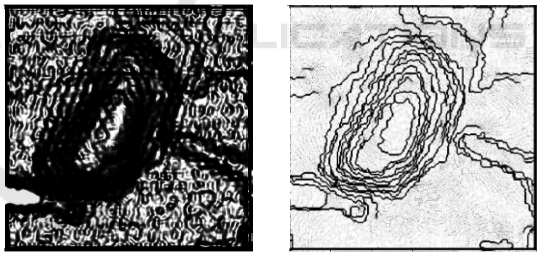
(a) (b)

Figure 11: Exudates extraction results for image 3th. (a) Exudates extraction results by the standard level set method. (b) Exudates extraction results by the hybrid of the K-means and level set methods.

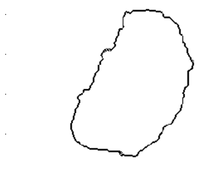


(a) (b)

Figure 12: Exudates extraction results for image 4th. (a) Exudates extraction results by the standard level set method. (b) Exudates extraction results by the hybrid of the K-means and level set methods.



(a) (b)



(c)

Figure 13: (a) The value of edge stopping of the reddish-greenish component after applying gaussian filter.b) The value of edge stopping of the reddish-greenish component after applying PMD filter. (b) The value of edge stopping of the reddish-greenish component after applying PMD filter and K-means algorithm.

the standard level set. The reason is that the value edge stopping function of the image in Figure 8 (a) (the proposed method) is high in other areas and small in the boundary areas as shown in Figure 13 (c). The level set contour will move from outside to inside when the edge stopping function has the high value and the level set contour will stop at the boundary areas. Figure 13 (a) shows the edge stopping function value of the standard level set. It takes low not only in the boundary areas but also in the other areas. It causes the level set contour stop prematurely in the evolution curve. This condition results unsatisfactory segmentation as shown in Figure 9 (a), Figure 10 (a), Figure 11 (a), Figure 12 (a). If the image is only filtered by the PMD filter, this problem also is happened. For this reason, the K-means needs to be run after applying the PMD filter.

However, the proposed method fails to differ the exudate areas and other areas in several areas as shown in Figure 9 (b), Figure 10 (b), Figure 11 (c) and Figure 12 (d). It is caused by the K-means algorithm cannot works well to differ the exudate areas and other areas. Since some exudate areas have similar color intensity with the non-exudate areas. To solve this problem, it needs to try other operation to enhance the quality of the fundus image.

5 CONCLUSIONS

It can be concluded that the hybrid of the PMD filter, the K-means and level set method works better in extracting the exudate areas on the fundus image than the standard level set method. In the evolution process of the level set, the curve of the level set stopped prematurely can be avoided by the hybrid of the PMD filter, the K-means and level set methods for almost all images used.

ACKNOWLEDGEMENTS

We would like to say our greatest thanks to the Directorate of Research and Community Service, Republic of Indonesia who has funded this research through the “Penelitian Dasar Unggulan Perguruan Tinggi (PDUPT)” in 2018.

REFERENCES

Airouche, M., Bentabet, L. Zelmat, M., 2009. Image segmentation using active contour model and level set method applied to detect oil spills. *Proceedings of the World Congress on Engineering* vol. I, pp. 1 - 3.

Anam, S., Uchino, E., Misawa, H., Suetake, N., 2013. Automatic bone boundary detection in hand radiographs by using modified level set method and diffusion filter. *Proceedings of the IEEE 6th International Workshop on Computational Intelligence and Applications*, Hiroshima, Japan, pp. 51−55.

Anam, S., Uchino, E., Misawa, H., Suetake, N., 2014a. Combining PSO and fuzzy inference for calculation of coronary plaque boundary in IVUS image. *International Journal of Biomedical Soft Computing and Human Sciences*, vol. 19, no. 1, pp. 51−59.

Anam, S., Uchino, E., Misawa, H., Suetake, N., 2014b. Retina vessels detection in fundus images by new morphology operation and the anisotropic diffusion filter. *Proceedings of the Annual Conference of Biomedical Fuzzy Systems Association*, pp. 39-40.

Barca, J. C., Rumantir, G., 2007. A modified K-means algorithm for noise reduction in optical motion capture data. *Procceeding of the 6th IEEE/ACIS International Conference on Computer and Information Science (ICIS 2007)*. doi:10.1109/icis.2007.29

Dhivya, A., Anitha, D., 2014. Detection of tumor region using fast fuzzy clustering algorithm. *International Journal of Research in Computer Applications and Robotics*, vol. 2, no. 4, pp. 145-149.

Li, C., Xu, C., Gui, C., Fox, M. D., 2010. Distance regularized level set evolution and its application to image segmentation, *IEEE Transactions on Image Processing*, vol.19, pp.3243-3254.

Li, Y. F., Zhu, Q. S. , Cao, Y. K. & Wang, C. L., 2005. A leaf vein extraction method based on snakes technique. *Proceedings of International Conference on Neural Networks and Brain*, pp. 885−888.

Madhukar, M., Manjula, D.Ujwal, Y., Deepthi, J., Seshacharan, S., 2017. Exudate extraction: a review. *Perspectives in Communication, Embedded-Systems and Signal-Processing*, vol. 1, no. 2, pp 8-9.

Mazid, K., 2013. *Segmentasi citra daun tembakau berbasis deteksi tepi menggunakan algoritma canny*. Thesis, Dian Nuswantoro University, Indonesia.

Osher, S., Sethian, J., 1998. Fronts propagating with curvature-dependent speed: algorithms based on Hamilton-Jacobi formulation. *Journal of Computational Physics*, vol. 79, pp. 12−49.

Pandey, P., Bhadauria, S. S., 2016. Removal of high density impulse noise using modified K-mean algorithm for digital image. *International Journal of Advance Research in Science and Engineering*, vol. 5, no. 05. pp. 465-473.

Perona, P. and Malik, J., 1990. Scale-space and edge detection using anisotropic diffusion. *IEEE Transactions on Pattern Analysis and Machine*

Intelligence, vol.12, pp.629 – 639.
Russ, J. C., 2006. *The image processing handbook*, *5th ed.* Academic Press, New York, 2006.
Santhi, M.V.B.T., Sai Leela, V.R.N.S.S.V., Anitha, P.U. Nagamalleswari, D., 2011. Enhancing K-means clustering algorithm. *International Journal of Computer Science and Technology*, vol. 2, no. 4., pp. 73-77.
Semeraro, F., Cancarini, A., Dell'Omo, R., Rezzola, S., Romano, M., and Costagliola, C., 2015. Diabetic retinopathy: vascular and inflammatory disease. *Journal of Diabetes Research*, pp. 1-16.
Soille, P., 1999. *Morphology image analysis: principles and applications.* Springer-Verlag, Telos.
Tarr, J. M., Kaul, K., Chopra, M., Kohner, E. M. And Chibber, R., 2013. Pathophysiology of diabetic retinopathy. *International Scholarly Research Notices Ophthalmology*, vol. 2013, pp. 1-13.
Tomasi, C., and Manduchi, R., 1998. Bilateral filter for gray and color images. *Proceeding of the 6th international Conference on Computer Vision,* pp. 839 – 846.
Weng, J. and Hu, G. 2017. Diabetes: leveraging the tipping point of the diabetes pandemic. *Diabetes*, vol. 66, pp. 1461-1463.