Segmentation of Blood Vessels in Retinal Images

Shashank Chary Avusali
Dept. of Computer Science
University of Missouri
Columbia, Missouri
Sa6y5@mail.missouri.edu

***Abstract*— In this project, a combination of matched filter with Gaussian, and first order derivative of Gaussian is used to segment the vessels in retinal images. Matched filtering with Gaussian has strong response to step edges along with blood vessels. To suppress these step edges, response of matched filtering with first order derivative of Gaussian is used to determine the segmentation threshold for each pixel. The experimental results shows a great improvement over the global thresholding of Matched filtering with Gaussian response.**

Keywords—vessel segmentation, matched filter; retinal images; first order derivative of Gaussian

I. Introduction

Structural changes of blood vessels in retinal images is a precursor for many diseases such as diabetic retinopathy[1], hypertension[2], [3], obesity, retinal artery occlusion, and cardiovascular stroke. For example, the presence of arteriovenous is a manifestation of stroke[4], changes in vessel tortuosity is a sign of hypertension. Early detection of these changes in vascular structures is needed to prevent the patients from major vision loss. Vessel segmentation plays a vital role in quantifying changes in tortuosity, branching angle. Traditional way to segment the vessels is to do it manually, where in an expert goes through the retinal images and classify each pixel as vessel or non-vessel. However, manual segmentation is time consuming, and you need an expert to segment the images. In addition to that, there exists an inter-expert variability, intra-expert variability in manually segmented images.

Automated segmentation provides a great alternative to manual segmentation. Such a segmentation is time efficient, helping the diagnosis of more patients with in a given period of time. Moreover, the segmentation of output of automated system is deterministic unlike manual segmentation where the segmentation results are non-deterministic.

II. Literature Review

Many methods have been proposed in the literature for detection and segmentation of blood vessels. Those methods can be mainly classified into three categories, filtering based approaches[5]–[7], tracking based[8], and machine learning approaches[8]–[10].

In filtering based approaches, a filter is created based on the characteristics of vessels. Retinal images are convolved with the filter, resulting in a maximum response at vessel locations, and low response at non-vessel locations in the output image. Most of these methods use angular scanning to detect vessel like structures. In [11] image is convolved with a two dimensional matched filter oriented in 12 different directions to enhance blood vessels. In [12], a similar approach is followed where the 17 filters oriented in 17 different directions were employed. In [13], a similar approach is adopted but the number of orientation has been reduced to 4. In [14], a non-linear filter that enhances vessels by exploiting properties of vessel profiles is introduced.

Tracking based approaches involves, detecting the center line of vessels based on the edge image. They incrementally detect and segment the vessels by utilizing the profile model. The performance of such methods is heavily reliant on the edge detection, and locating the starting points for tracking.

Machine learning methods are further classified into supervised methods, and unsupervised methods. In supervised methods a model is trained with a pre-segmented data set. The trained model is further used to segment images that are not already segmented. On the other hand, unsupervised methods does not require and pre-segmented images, tries to segment the images based on vessel characteristics such as pixel intensity. A neural network is trained in [15] to segment the images. The feature vectors are constructed using the local neighborhood of the pixel being classified. In [10], original grey level of the green channel image combined with the outputs of multi scale Gaussian filters are given as input to a k-nearest neighborhood classifier.

The remainder of the paper is organized as follows. Section III reviews two dimensional matched filtering with Gaussian, and first order derivative of Gaussian along with preprocessing and post processing applied in this project. Results of applying specified methods on publicly available DRIVE database is presented in section IV. Detailed analysis of results is explained in section V. Section VI concludes the report.

III. Methods

As proposed in [16] I have used two dimensional matched filter with Gaussian (MF-G), and first order derivative of Gaussian (MF-FDOG) to segment blood vessels in retinal images. The Gaussian filter is used to enhance the blood vessels, whereas the response of first order derivative of Gaussian is used to determine the local threshold for segmenting MF-G response.

Green channel of a retinal image is widely used for automatic segmentation, considering its high contrasts between vessels and background. The green channel image is inverted to make the vessels brighter, and background darker. In all of the experiments, inverted green channel images of retinal images are used. Figure 1 shows the inverted green channel image from one of the DRIVE database images.

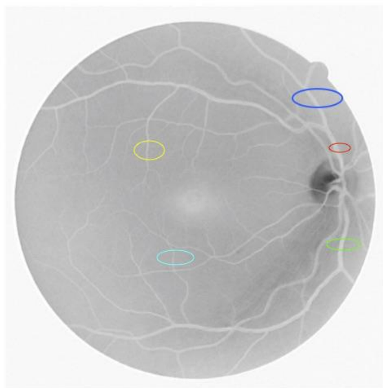

Figure 1: Inverted Green channel retinal image

The following subsections gives the reader an overview of various steps employed in this project to detect blood vessels.

A. Pre-processing

The retinal images have uneven illumination, called vignetting [6]. This is due to improper focus of light through optical system. As a result, the brightness of image decreases as we move away from the center of the image. To correct vignetting, a smoothed version of the image is subtracted from the inverted green channel image. Figure 2 shows normalized image after illumination correction, the non-normalized image was harder to visualize, normalized image has been displayed just to illustrate the effect of preprocessing. It can be seen that the blood vessels in Figure 2 appear brighter than the vessels of Figure 1. In this project images without normalization are used for further processing.

Figure 2: Normalized image after vignetting correction of Figure 1

B. Matched Filter with Gaussian

Two dimensional matched filtering with Gaussian [11] is one of the classical methods for vessel extraction from retinal images. It is based on the observations that the blood vessels can be approximated by piecewise linear structures, gray level profile along directions perpendicular to their length may be approximated by a Gaussian.

The cross-sectional intensity profiles of various vessels from Figure 1 are plotted in Figure 3. It is observed that the vessels almost never have ideal step edges, intensity of vessel decreases as we move perpendicularly away from the center line of the vessel. It can also be observed that the intensity profile curve may be approximated by Gaussian. Therefore, a Gaussian-shaped filter can be used to match the vessel for detection.

The MF-G filter is defined as

$$f(x,y) = \frac{1}{\sqrt{2\pi s^2}} e^{\left(-\frac{x^2}{2s^2}\right)}, \text{ for } |x| \leq 3s,\ |y| \leq \frac{L}{2} \quad (1)$$

Where s represents the scale of the filter, L is the length of the segment for which the vessel is assumed to have fixed orientation.

To remove the smooth background, the filter is normalized to have zero mean by subtracting its mean.

$$f'(x,y) = f(x,y) - m \quad (2)$$

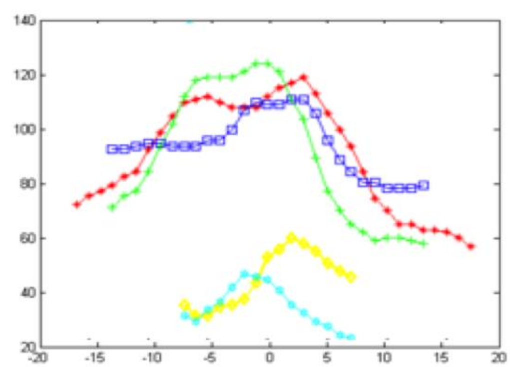

Figure 3: Cross-sectional intensity profile of blood vessels from Figure 1

Where m is the mean of the filter calculated as

$$m = \frac{\int_{-3s}^{3s} \frac{1}{\sqrt{2\pi s^2}} e^{\left(-\frac{x^2}{2s^2}\right)} dx}{2\times 3s} \quad (3)$$

With MF-G filter, most of the thin and thick vessels can be identified by varying the value of s. Filter with lower value of s would detect thin vessels, high value of s is used to detect thick vessels. However, the MF-G gives strong response not only to blood vessels but also to step edges. This can be illustrated in Figure 4. It can be observed from Figure 4(b2) that, the MF-G filter has strong response for synthetic Gaussian signal, it has partially strong positive response for synthetic step edge signal. If we apply a threshold T to MF-G output h to detect vessels, some of the non-vessel pixels would be classified as vessels.

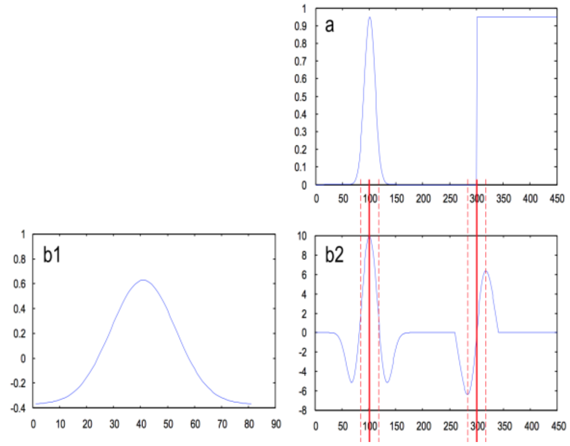

Figure 4: a) Synthetic signals of vessel and step edge. b1) Gaussian filter. b2) Response of filter (b1) for signals of (a)

C. Matched filter with FDOG

To overcome the drawback of MF-G filter, the authors of [16] proposed matched filtering with MF-FDOG filter. This is based on the fact that the response of MF-FDOG to Gaussian signal is anti-symmetric, response to step edge is positive and symmetric. This is illustrated in Figure 5.

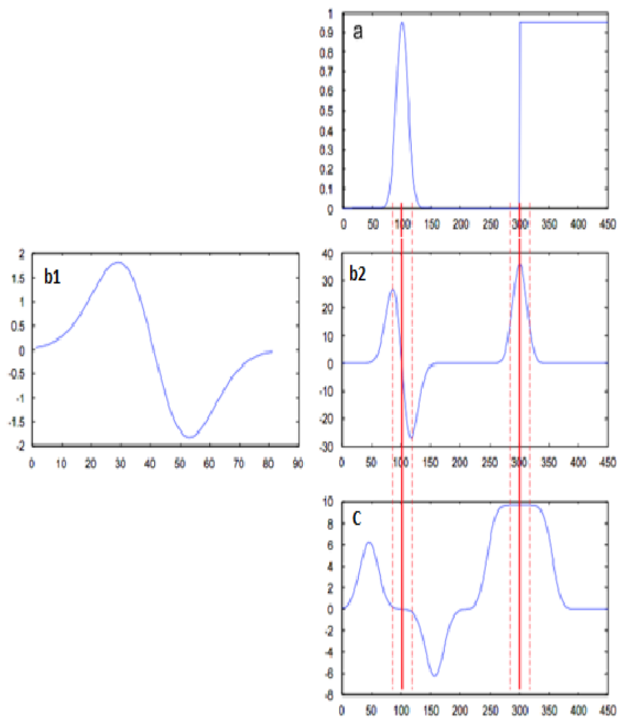

Figure 5: a) Synthetic signals of vessel and step edge. b1) FDOG filter. b2) Response of filter (b1) for signals of (a)

The authors of [16] made use of the response of FDOG filter d, to determine the threshold for each pixel in h, MF-G filter output. Consider the local mean of d, denoted by d_m, it would have strong responses to step edge. Whereas, the response to a vessel in d_m would be very low. This information is used to threshold h, resulting in high threshold value for pixels surrounding a step edge, low threshold value for pixels surrounding a blood vessel.

The FDOG filter is defined as

$$g(x,y) = \frac{-x}{\sqrt{2\pi}s^3} e^{(-\frac{x^2}{2s^2})} - m \qquad (4)$$

Where m is now given as

$$m = \frac{\int_{-3s}^{3s} \frac{-x}{\sqrt{2\pi}s^3} e^{(-\frac{x^2}{2s^2})} dx}{2\times 3s} \qquad (5)$$

A thresholding scheme was proposed in [16]

$$T = (1 + d_m)T_C \qquad (6)$$

Where T_C is a reference threshold, set as follows based on mean response of h, μ_h.

$$T_c = c.\mu_h \qquad (7)$$

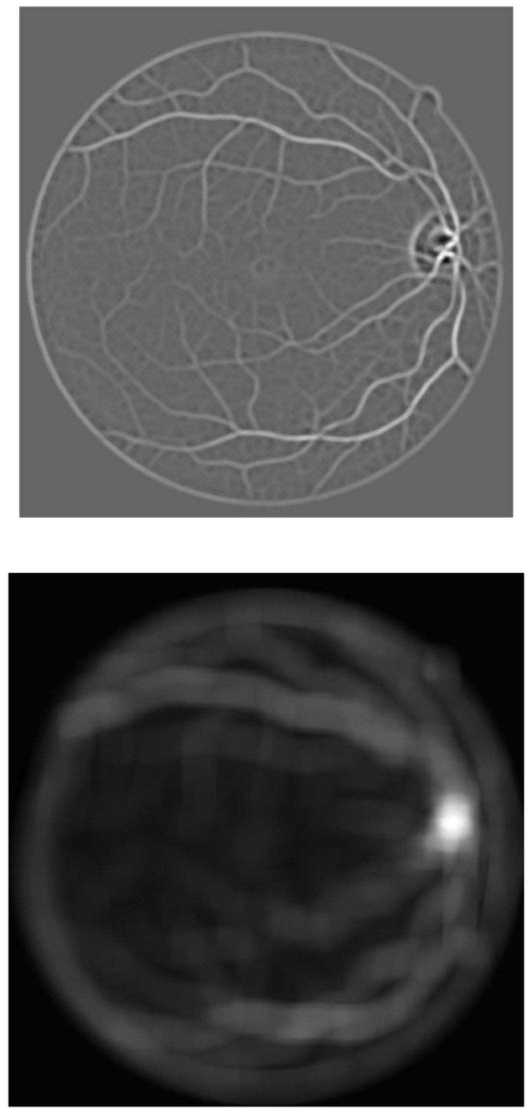

Figure 6: upper: response of matched filtering with Gaussian, lower: response of matched filtering with first order derivative of Gaussian

In Figure 6, the upper figure shows the fused response of matched filtering with Gaussian for scales 1.5 and 2. The lower figure illustrates the fused response of matched filtering with first order derivative of Gaussian.

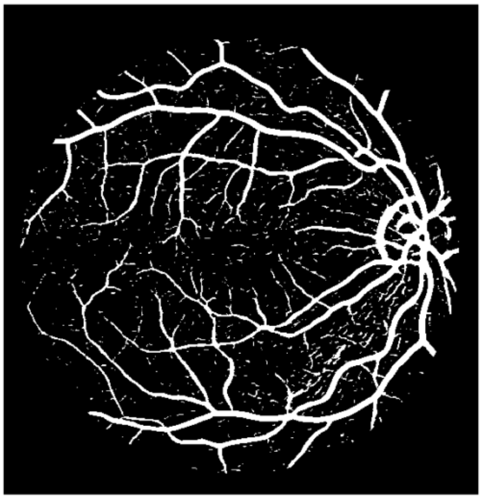

Figure 7: Segmentation, as a result of thresholding based on equation 7

D. Post-processing

The segmentation result can be seen in Figure 7. There is a lot of speckle noise in the segmented image. Mathematical morphology has been used to remove the noise. In particular, connected component analysis has been performed on the binary image, the components whose area is less than 20 pixels is removed. Figure 8 shows the binary image after post processing. As it can be noticed, this step has reduce a lot of false positives.

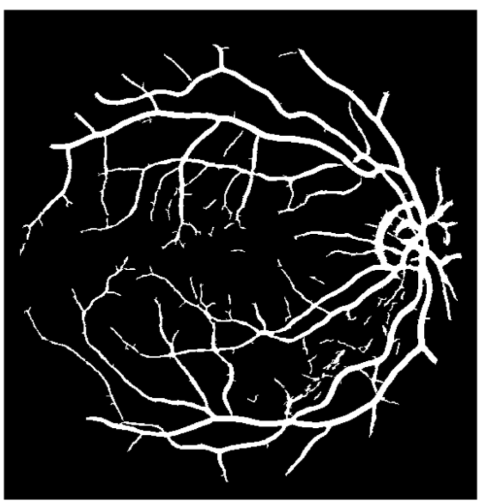

Figure 8: Segmented image after post processing

IV. Results

To extract the vessels oriented in different direction, the preprocessed image is convolved with the Gaussian filter in 8 different orientations, $-90°$ to $+30°$. To extract thin and thick vessels, the scale parameter is set to 1.5 and 2 respectively. Responses from 16 filters are fused by taking max response value for each pixel to get a final image, h. Preprocessed image is convolved with FDOG filter oriented in 8 different directions, same as Gaussian filter. Responses from 16 filters are fused by taking max response value for each pixel to get a final image, d. Image d is convolved with mean filter of size 31×31filter to get d_m. The value of c is set to 1.

In this project I have tested the MF-DOG filter on one of the publicly available database, DRIVE. The DRIVE database consists of 40 images captured by the Canon CR5 camera at $45°$ FOV, which are digitized at 24 bit with a spatial resolution of 565×584 pixels. The 40 images are divided into a training set and a test set by the authors of the database. The results of the manual segmentation are available for train and test sets.

Figure 9 and 10 shows the results of segmentation with MF-G and MF-FDOG filter on one of the other image from DRIVE database. According to my understanding and implementation, their proposed method was able to detect most of the thin and thick vessels.

V. Discussion

The authors of [16] used accuracy, true positive rate (TPR), false positive rate (FPR) as quantitative metrics to evaluate the performance of their method. Where the metrics are defined as follows:

$$Accuracy = \frac{\#\ correctly\ classified\ pixels}{\#pixels\ in\ FOV}$$

Figure 9: Another retinal image from DRIVE database

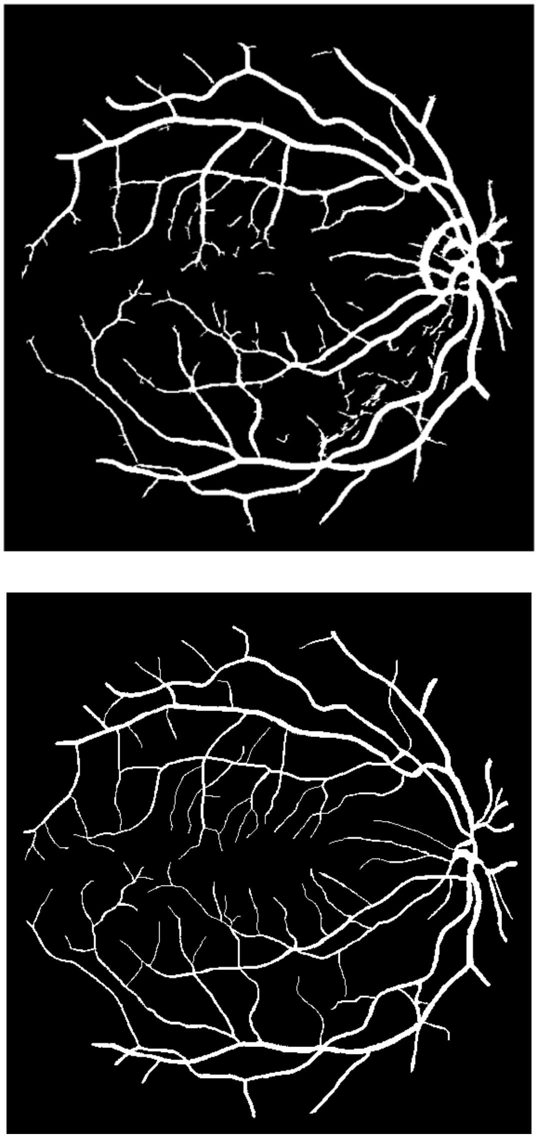

Figure 10: upper: Segmentation result of method implemented in project, lower: Image segmented by human expert.

$$TPR = \frac{\#\ correctly\ classified\ vessel\ pixels}{\#vessel\ pixels\ in\ ground\ truth}$$

$$FPR = \frac{\#\ Non\ vessel\ pixels\ classified\ as\ vessel\ pixels}{\#Non - vessel\ pixels\ in\ FOV\ in\ ground\ truth}$$

Experimental results on DRIVE database are presented in Table 1. The performance measures for different methods listed in the table are obtained from [16]. As a part of this project, I have calculated the same quantitative metrics. The experimental results show that thresholding based on MF-FDOG response has greatly improve the vessel detection. The implemented method was able to detect many methods that the matched filter might miss.

Method	***TPR***	***FPR***	***Accuracy***
2nd Human Observer	0.7761	0.0275	0.9473
Matched filter [11]	0.6168	0.0259	0.9284
[16]	0.7120	0.0276	0.9382
This project	0.7083	0.0458	0.9236

VI. CONCLUSION

A method for blood vessel segmentation in retinal images based on matched filtering with Gaussian, and first order derivative of Gaussian is implemented as a part of this project. The results obtained on DRIVE database show that the implemented method was able to detect more vessels than the [11]'s matched filtering with Gaussian.

VII. REFERENCES

[1] E. J. Sussman, W. G. Tsiaras, and K. A. Soper, "Diagnosis of Diabetic Eye Disease," *JAMA J. Am. Med. Assoc.*, vol. 247, no. 23, p. 3231, Jun. 1982.

[2] A. V Stanton, B. Wasan, A. Cerutti, S. Ford, R. Marsh, P. P. Sever, S. A. Thom, and A. D. Hughes, "Vascular network changes in the retina with age and hypertension.," *J. Hypertens.*, vol. 13, no. 12 Pt 2, pp. 1724–8, Dec. 1995.

[3] T. Y. Wong and R. McIntosh, "Hypertensive retinopathy signs as risk indicators of cardiovascular morbidity and mortality," *Br. Med. Bull.*, vol. 73–74, no. 1, pp. 57–70, Oct. 2005.

[4] T. Y. Wong, R. Klein, D. J. Couper, L. S. Cooper, E. Shahar, L. D. Hubbard, M. R. Wofford, and A. R. Sharrett, "Retinal microvascular abnormalities and incident stroke: the Atherosclerosis Risk in Communities Study," *Lancet*, vol. 358, no. 9288, pp. 1134–1140, Oct. 2001.

[5] M. G. Cinsdikici and D. Aydın, "Detection of blood vessels in ophthalmoscope images using MF/ant (matched filter/ant colony) algorithm," *Comput. Methods Programs Biomed.*, vol. 96, no. 2, pp. 85–95, Nov. 2009.

[6] A. Hoover and M. Goldbaum, "Locating the optic nerve in a retinal image using the fuzzy convergence of the blood vessels," *IEEE Trans. Med. Imaging*, vol. 22, no. 8, pp. 951–958, Aug. 2003.

[7] M. Al-Rawi, M. Qutaishat, and M. Arrar, "An improved matched filter for blood vessel detection of digital retinal images," *Comput. Biol. Med.*, vol. 37, no. 2, pp. 262–267, 2007.

[8] Y. A. Tolias and S. M. Panas, "A fuzzy vessel tracking algorithm for retinal images based on fuzzy clustering," *IEEE Trans. Med. Imaging*, vol. 17, no. 2, pp. 263–273, Apr. 1998.

[9] J. Staal, M. D. Abramoff, M. Niemeijer, M. A. Viergever, and B. van Ginneken, "Ridge-Based Vessel Segmentation in Color Images of the Retina," *IEEE Trans. Med. Imaging*, vol. 23, no. 4, pp. 501–509, Apr. 2004.

[10] M. Niemeijer, J. Staal, B. Van Ginneken, M. Loog, and M. D. Ab Amoff Abc, "Comparative study of retinal vessel segmentation methods on a new publicly available database."

[11] S. Chaudhuri, S. Chatterjee, N. Katz, M. Nelson, and M. Goldbaum, “Detection of blood vessels in retinal images using two-dimensional matched filters,” *IEEE Trans. Med. Imaging*, vol. 8, no. 3, pp. 263–269, 1989.

[12] J. V. B. Soares, J. J. G. Leandro, R. M. Cesar, H. F. Jelinek, and M. J. Cree, “Retinal vessel segmentation using the 2-D Gabor wavelet and supervised classification,” *IEEE Trans. Med. Imaging*, vol. 25, no. 9, pp. 1214–1222, Sep. 2006.

[13] A. M. Mendonca and A. Campilho, “Segmentation of retinal blood vessels by combining the detection of centerlines and morphological reconstruction,” *IEEE Trans. Med. Imaging*, vol. 25, no. 9, pp. 1200–1213, Sep. 2006.

[14] J. Lowell, A. Hunter, D. Steel, A. Basu, R. Ryder, and R. L. Kennedy, “Measurement of Retinal Vessel Widths From Fundus Images Based on 2-D Modeling,” *IEEE Trans. Med. Imaging*, vol. 23, no. 10, pp. 1196–1204, Oct. 2004.

[15] C. Sinthanayothin, J. F. Boyce, H. L. Cook, and T. H. Williamson, “Automated localisation of the optic disc, fovea, and retinal blood vessels from digital colour fundus images.,” *Br. J. Ophthalmol.*, vol. 83, no. 8, pp. 902–10, Aug. 1999.

[16] B. Zhang, L. Zhang, L. Zhang, and F. Karray, “Retinal vessel extraction by matched filter with first-order derivative of Gaussian,” *Comput. Biol. Med.*, vol. 40, no. 4, pp. 438–445, 2010.