# Identifying the Optimal Threshold for Image Segmentation Using PSO and Its Application to Chronic Wound Assessment

Wanyok Atisattapong, Chontida Chansri, Jidapa Somboonbadeebut, and Pakorn Songkaew
Department of Mathematics and Statistics, Faculty of Science and Technology, Thammasat University, Pathum Thani, Thailand
Email: awanyok@tu.ac.th, {chontidaf, m.jidapas, pakornsbank}@gmail.com

***Abstract*—In this paper we propose an improved procedure for Chronic Wound (CW) assessment. First, the optimal threshold for segmenting the wound area from the background is selected. This is done using a combination of Otsu's method and Particle Swarm Optimization (PSO). The color features of the image are then extracted using K-means clustering to monitor the progression of wound healing. Fifty CW images from the Medetec medical image database were analyzed to compare the efficiency of the proposed method with that of the traditional Otsu method. The proposed method achieved improved image segmentation in 46% of cases, while in 16% quality was unchanged and in 38% quality was degraded. We also demonstrated the application of K-means clustering to classification of wound tissue. This allows the progression of tissue repair to be assessed and impaired healing to be identified via a telemedicine system, of particular salience in remote areas where clinical expertise in wound management is lacking.**

***Index Terms*—swarm intelligence, image processing**

## I. Introduction

Many hospitals are limiting visits to reduce the risk of COVID-19 infection. This has profoundly affected nursing and has negatively impacted the provision of necessary medical care. The specialty of Chronic Wound (CW) healing has been especially impacted. CW patients often remain too long in the inflammatory stage and take too long to heal. They need comprehensive care to prevent potential complications. However, recurrent hospital visits expose patients to increased risk of infection. As it is difficult to arrange appointments with specialists, waiting times can be long.

Telemedicine has rapidly evolved as a tool for providing remote healthcare. It can connect patient and doctor more effectively, allowing the specialist to make improved diagnoses via remote imaging. However, the medical images may be of insufficient quality. Improved image processing is particularly important in assessment of CWs. The analysis relies heavily on image segmentation. In this work, we suggest an approach to the improvement of the traditional Otsu algorithm that incorporates swarm intelligence optimization to discover the optimal threshold for image segmentation.

A chronic wound is one that has failed to progress through the phases of healing in an orderly and timely fashion and which fails to show significant healing within four weeks [1] This is often due to underlying conditions or disorders, and these need to be addressed with additional medical care. The most common underlying causes include diabetes, vascular disease (peripheral artery disease), limited mobility, repeated trauma to wound site, infection-causing bacteria (staphylococcus aureus), and edema (swelling).

Most wounds will contain a mix of tissue types at any one stage, and assessment must estimate the relative percentages. They are commonly classified into three major types: necrosis, slough, and granulation [2]. The progress of wound healing can be assessed by considering the percentage of each. If the wound is healing as expected, the granulation percentage should decrease [3]. In this study we first obtained accurately segmented images of the CW, then applied K-means cluttering to extract color features. These data support wound tissue classification.

## II. Literature Review

Otsu [4] introduced an algorithm that automatically determines an image's threshold. This method is based on discriminant analysis, which can be calculated from a grayscale image. It is nonparametric and unsupervised. The algorithm was used to identify a threshold for images of an identical character "A", typewritten in different faces and textures. The algorithm was shown to efficiently select an optimal threshold.

Kennedy and Eberhart [5] proposed an optimization technique called Particle Swarm Optimization (PSO). This has received wide attentions in recent years [6]. It mimics the social behavior of foraging herds, such as flocks of birds or fish swarms. In PSO, each particle is assigned a velocity and location. These are updated by applying fitness values and searching for an optimal solution. This process is repeated until the optimal solution is found or a predetermined cycle is completed. The final best position counts as a solution.

Manuscript received November 29, 2021; revised May 19, 2022.


doi: 10.18178/joig.10.3.116-121

Jianzhuang, Wenqing, and Yupeng [7] extended Otsu's one-dimensional method to two dimensions, to address images in which the object size is very different from the background. The two-dimensional method utilizes the gray-level of each pixel and its spatial correlation within the neighbourhood, whereas the one-dimensional method uses only gray-level information for each pixel. The two-dimensional method was shown experimentally to offer much improved performance. Wei *et al.* [8] presented an improved two-dimensional Otsu algorithm which used PSO (TOPSO) to search for the optimal threshold for image segmentation. They applied this to segmentation of raw pictures and compared the performance of the Otsu and TOPSO approaches. They demonstrated that this approach is a simple and effective method for gray-level image segmentation, with reduced computation cost.

Dubey *et al.* [9] presented a novel segmentation method for identifying defects in fruits based on color features, by applying an unsupervised K-means clustering algorithm [10]. Defective apples were used as a case study. The experimental results confirmed that the approach was able to accurately segment the defective areas present in the image. Permula and Raju [11] investigated the optimal threshold for improving the segmentation of low-contrast images. Fuzzy logic was applied to select the optimal threshold value for use in the Otsu method. The experimental data confirmed that this method improved the contrast, giving better results than either the traditional Otsu or fuzzy logic techniques.

Chakraborty [12] analyzed four different ulcerous cases from the Tele-wound network to identify efficient filtering techniques for chronic wound image pre-processing. Different filtering techniques exhibited differences in performance. An adaptive median filter performed best for noise removal. The wound regions were then segmented using PSO in the Dr and Db color channels. The PSO algorithm provided better accuracy in segmentation, and sensitivity in the Db channel. Linear Discriminant Analysis (LDA) classification was used to distinguish the wound tissues. LDA was shown to classify the tissues with satisfactory accuracy. Chakraborty [2] developed this approach by applying fuzzy clustering. Two-step pre-processing was applied before image segmentation. First, a median filter eliminated unwanted noise. The contrast for the specified channel was then computed, and the image segmented in a high-contrast color channel. Fuzzy c-means clustering was then used to segment the image. The efficiency of different techniques for classifying wound tissue was also compared: LDA, naive basilica, decision trees, and random forests. Random forests provided the highest classification accuracy.

Yanqiao *et al.* [13] proposed a fast 2D Otsu lung tissue image segmentation algorithm based on an improved PSO. A threshold obtained by the proposed method and runtime were compared with the deep fully convolutional residual network method and the traditional Otsu method. The results showed that the proposed method can satisfy the requirements of segmentation precision and operation speed. Lingeswari *et al.* [14] use a color thresholder technique and K-means clustering in images segmentation to detect diseases in tomatoes. Three factors including mean, variance, and SNR were compared to test an efficiency. It found that K-means clustering is better than the color thresholder method for detecting tomato diseases.

## III. METHOD

Fig. 1 gives an overview of the three steps in our framework.

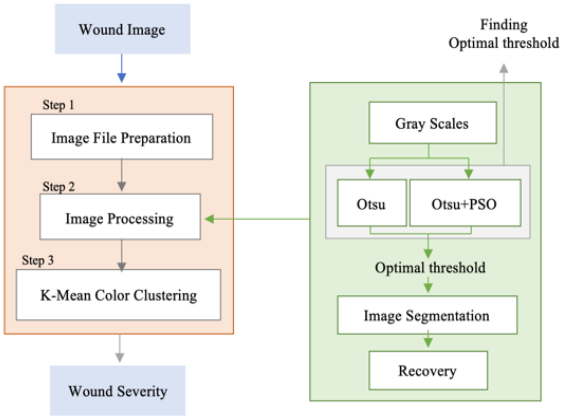



Figure 1. Overview framework.

### A. *Image File Preparation*

CW images were extracted from the Medetec medical image database (https://www/medetec.co.uk/files/mede). A web scraping algorithm read the URLs and automatically saved the images as .jpg files. These were stored as "/content" files in Google Collab. Fifty images of chronic wound types were selected, including pressure, venous, and arterial ulcers, burns and scalds, and orthopedic wounds. The full list is presented in Table I. The selection criteria were: i) the wound presents an overall appearance that is clear and well-lit, ii) no necrosis is present, and iii) the wounds affect a range of different organs.

TABLE I. WOUND TYPE

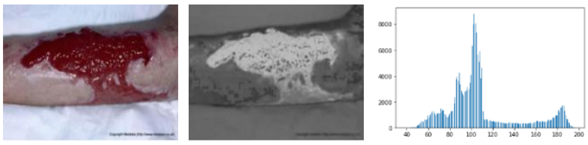
| Type | Number of Images |
|---|---|
| 1) Pressure ulcer | 8 |
| 2) Venous and arterial ulcer | 8 |
| 3) Burn and scald | 7 |
| 4) Meningitis | 7 |
| 5) Miscellaneous wounds | 6 |
| 6) Orthopedic wound | 4 |
| 7) Diabetic foot ulcer | 3 |
| 8) Infected and necrotic toes | 2 |
| 9) Malignant wound | 2 |
| 10) Hemangioma | 2 |
| 11) Pilonidal sinus wound | 1 |
| **Total** | 50 |

### B. *Image Processing*

Before assessing the severity of the wound, four-stage image processing was conducted.

*1) Grey scale image*

When retrieved from the database the image is in RBG color. It is converted to the HSV system for clarity, then to grayscale, which comprises 256 shades (from 0 for black to 255 for white). A histogram representing the density of shades is obtained. Fig. 2 is an example of the wound image after conversion.



(a) (b) (c)

Figure 2. (a) Original image, (b) grayscale image, and (c) histogram of grayscale.

*2) Finding optimal threshold*

Otsu's [8] is a simple and popular automatic thresholding method for the pixels of a given picture in $L$ gray-levels $[0, 1, 2, \ldots, L-1]$. The number of pixels at level $i$ is denoted by $n_i$ and the total pixels by $N = n_0 + n_1 + \ldots + n_{L-1}$. The gray-level histogram is normalized as a probability distribution function [9].

$$p_i = \frac{n_i}{N}, p_i \geq 0, \sum_{i=0}^{L-1} p_i = 1 \tag{1}$$

Suppose that $k$ is the threshold value. The pixels are divided into two classes: background (class 1) denoted by pixels with $[0, 1, \ldots, k-1]$ and objects (class 2) denoted by pixels with $[k, k+1, \ldots, L-1]$. The normalized fractions of pixels are then defined by:

$$\omega_1 = \sum_{i=0}^{k-1} p_i \text{ and } \omega_2 = 1 - \omega_1 \tag{2}$$

The background and object means of a gray-level image are calculated as:

$$\mu_1 = \frac{\sum_{i=0}^{k-1} ip_i}{\omega_1} \text{ and } \mu_2 = \frac{\sum_{i=k}^{L-1} ip_i}{\omega_2} \tag{3}$$

The total mean of the gray-level image is calculated as:

$$\mu_T = \sum_{i=0}^{L-1} ip_i \tag{4}$$

The background and object variance of the gray-level are calculated as:

$$\sigma_1^2 = \sum_{i=0}^{k-1} \left(i - \mu_1\right)^2 \frac{p_i}{\omega_1} \tag{5}$$

$$\sigma_2^2 = \sum_{i=k}^{L-1} \left(i - \mu_2\right)^2 \frac{p_i}{\omega_2} \tag{6}$$

Next, the within-class, between-class, and total variances of the gray-level image are calculated as:

$$\sigma_W^2 = \omega_1 \sigma_1^2 + \omega_2 \sigma_2^2 \tag{7}$$

$$\sigma_B^2 = \omega_1 \left(\mu_1 - \mu_T\right)^2 + \omega_2 \left(\mu_2 - \mu_T\right)^2 \tag{8}$$

$$\sigma_T^2 = \sum_{i=0}^{L-1} \left(i - \mu_2\right)^2 p_i \tag{9}$$

Otsu's method can be represented in pseudocode as follows.

**Algorithm 1:** Traditional Otsu's method

```
INPUT: An image with 256 gray-levels
OUTPUT: Optimal threshold
For i = 0:L (maximum intensity level) do
    Update class weights ω_1(i) and ω_2(i) by Eq. (2)
    Update class means μ_1(i) and μ_2(i) by Eq. (3)
    Compute variances within class σ_w(i) by Eq. (7)
    Compute variances between classes σ_B(i) by Eq. (8)
    If σ_B(i) > max{ {σ_B(0), ..., σ_B(i − 1)} } then
        Set threshold as i, threshold = i
    End
End
Return threshold
```

The PSO algorithm [6] was then implemented to improve the traditional Otsu method. This randomly sets an initial position and velocity for each particle in the search area. The fitness value of the particle is evaluated at each iteration. If the value is optimal for that particle, it is stored as *pbest* (particle best). The optimal *pbest* in any iteration is stored as *gbest* (global best). The velocity and position are updated by Eqs. (10) and (11):

$$\begin{aligned} V_i^{t+1} &= wV_i^t + C_1 rand(\ )\left(pbest_i - X_i^t\right) \\ &+ C_2 rand(\ )\left(gbest - X_i^t\right) \end{aligned} \tag{10}$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \tag{11}$$

here $V_i^{t+1}$ is the velocity of the particle, $X_i^{t+1}$ is its current position, $rand(\ )$ is a random number between 0 and 1, $C_1$ and $C_2$ are learning factors, and $w$ is the inertia weight.

The fitness function of the Otsu method is used to find the greatest variance between classes. Eqs. (3), (5) and (6) can be rewritten as follows:

$$\mu_1 = \frac{\sum_{i=1}^{k-1} ip_i}{\omega_1 + 1} \text{ and } \mu_2 = \frac{\sum_{i=k}^{L-1} ip_i}{\omega_2 + 1} \tag{12}$$

$$\sigma_1{}^2 = \sum_{i=0}^{k-1} \left(i - \mu_1\right) \frac{p_i}{\left(\omega_1 + 1\right)} \tag{13}$$

$$\sigma_2{}^2 = \sum_{i=k}^{L-1} (i - \mu 2) \frac{p_i}{\left(\omega_2 + 1\right)} \tag{14}$$

Eqs. (8) and (9) were used to calculate the measures of class separability:

$$\eta = \frac{\sigma_B{}^2}{\sigma_T{}^2} \tag{15}$$

**Algorithm 2:** Propose Otsu with PSO

```
INPUT: An image with 256 gray levels
OUTPUT: Optimal threshold
Set initial parameters (Particlesize = 20, bound = [0,255],
maxiteration = 20, w=0.85, c1=2.05, pbest=-∞, gbest=-∞)
For i=1: Particlesize do
  | randomly initialize each particle position Xi and
  | velocities Vi
End
For t=1: maxiteration do
  For i=1: Particlesize do
    Evaluate the fitness function of Particle_i by Eq. (15)
    If fitness value better than pbest in history then
      Set current fitness value to be pbest,
      Pbest_i = fitness value
    End
    If pbest_j better than gbest then
      Set pbest_j to be gbest, gbest = pbest_j
      Set threshold as position X_i, threshold = X_i
    End
  End
  For i=1: Particlesize do
    Update the velocity of Particle_i, V_i, by Eq. (10)
    Update the position of Particle_i, X_i, by Eq. (11)
    If X_i more than bound then
      | Set X_i as the upper bound
    Else X_i less than bound then
      | Set X_i as the lower bound
    End
  End
End
Return threshold
```

*3) Image segmentation*

We segment the image using Binary Image Segmentation, a method for classifying pixels into two colors by comparing the grayscale value of each pixel and the threshold value derived in the previous section. If the pixel has a grayscale value greater than or equal to the threshold value it is converted to white; if the pixel has a grayscale value less than the threshold value it is converted to black. After all pixels have been converted, the resulting a binary image is segmented such that the foreground objects are white while the remainder of the image is black.

*4) Image color recovery*

After image segmentation, the original color is restored by multiplying the binary image by the original RGB values.

### *C. K-Mean Color Clustering*

Using the results obtained from this step, the shades are placed into eight groups using K-mean clustering. The K-mean clustering [10] algorithm works as follows:

Step 1 Select a number $K$ to enumerate the clusters and randomize the centroids for each cluster $K$.

Step 2 Assign each data point to its closest centroid. The Euclidian distance is used to determine the distance between each data object and the centroid.

Step 3 Calculate the variance and give each cluster a new centroid.

Step 4 Recalculate the cluster.

Step 5 If the new cluster is same as that in the previous iteration, this is the final grouping. If not, the process is repeated.

In our study, the pixel intensities of an RGB image with $M \times N$ pixels are clustered using K-means. We use $K=8$ as this is sufficient to obtain all the main shades in the selected image. To facilitate analysis and evaluation, eight groups from the K-means are classified into four shades: (1) black for the background, (2) red for fresh wounds, (3) pink for a wound area that is almost completely healed, and (4) other parts of the background that cannot be removed by image segmentation.

## IV. RESULTS

The algorithm was implemented in Python. Fifty images from Medetec were used to compare the performance of the traditional Otsu method with the proposed method. The criteria for performance assessment were as follows:

a) The image is segmented close to the edge of the wound.
b) The background is removed completely, and the removed part can be viewed as a single continuous area.

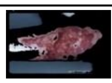
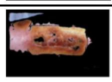
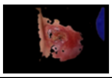
### *A. Image Segmentation*

To compare the proposed method with the traditional Otsu method, three criteria were used (Table II).

TABLE II. RESULTS FROM EFFICIENCY COMPARING

| Efficiency | Number of Images | Percentage |
|---|---|---|
| 1) Improved image segmentation | 33 | 46% |
| 2) Degraded segmentation | 19 | 38% |
| 3) Unchanged quality | 8 | 16% |
| Total | 50 | 100% |

TABLE III. RESULTS: TRADITIONAL OTSU AND PROPOSED OTSU

| Image Name | Original Images | Traditional Otsu | Proposed Otsu with PSO |
|---|---|---|---|
| M1 |  |  |  |
| M2 |  |  |  |
| M3 |  |  |  |
| M4 |  |  |  |
| M5 |  |  |  |
| M6 |  |  |  |

*CASE 1: Improved image segmentation.* As can be seen from Table III, for Images M1 and M2 the proposed

method with PSO segmented the wound area from the background more clearly than the traditional Otsu method. This improvement in image segmentation was most pronounced when applied to images with the following properties:

i) The area of skin and wound is close in size to that of the background, while the two parts are distinct in shade.
ii) Most areas of the image have uneven texture.
iii) The skin and the wound are very similar in shade.
iv) A close-up image clearly shows the skin surrounding the wound.

When these conditions are satisfied, the proposed method is able to segment the image closer to the edge of the wound and more effectively remove the background.

*CASE 2: Degraded segmentation.* Table III shows that, for Images M3 and M4, the traditional Otsu method segmented the wound area from the background more clearly than the proposed method with PSO. The latter is inferior to the traditional Otsu method when applied to images with the following properties:

i) The area of skin and wound is greater than the area of the background.
ii) The image has bright spots.
iii) The wound has a yellow shade.

Under these circumstances, the proposed method was unable to segment the image close to the edge of the wound. The background was not removed as a continuous area, and less was removed than when using the traditional Otsu method.

*CASE 3: Unchanged quality.* For images M5 and M6 (Table III) the proposed method and the traditional Otsu method yielded the same results. In the case of M5, most of the image area was uneven in texture and contained bright spots. In the case of M6, the skin and wound occupied almost the same area as the background, although the two parts were of distinct shades. The image also contained areas of slough tissue, which are of yellow shade. In this case some properties of the image were improved, and others degraded.

## *B. K-Means Classification*

The K-means method was used to cluster the image color. An example result can be seen in Fig. 3.

(a) (b) (c)

Figure 3. (a) Original wound image, (b) result from Image Segmentation, and (c) shade grouping using K-means.

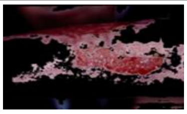
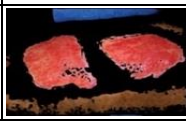
In Fig. 3(a) shows the original image, Fig. 3(b) shows the result after image segmentation by the proposed method, and the pie chart Fig. 3(c) compares eight color shades.

We set $K$=8 to allow most shades to be extracted from the image. Recovery can be monitored by the percentage of shades that change. We grouped these into four: background, fresh wound, almost completely healed wound, and others. In Fig. 3 the image is 61.83% black (Shade 1), which determines the background area. In this case, it is the largest area. The area of fresh wound is indicated by red (Shade 2). In this image, it comprises only 0.55% of the total. Shades 3 and 4 are the area of almost completely healed wound. These occupy 4.72% and 7.28%, summing to approximately 12% of the total. Remaining areas that are neither background nor wound are shown by Shades 5-8, which together account for 25.62% (the sum of 4.10, 5.77, 5.26, and 10.49%). The proportions of each group are shown in Table IV.

TABLE IV. GROUPING THE SHADES INTO FOUR CLASSES

| Shade | Percentage of shade | Class | Percentage of class |
|---|---|---|---|
| 1 | 61.83 % | 1 Background | 61.83 % |
| 2 | 0.55 % | 2 Fresh wound | 0.55 % |
| 3 | 4.72 % | 3 Almost completely healed wounds | 12.00 % |
| 4 | 7.28 % | | |
| 5 | 4.10 % | 4 Others | 25.62 % |
| 6 | 5.77 % | | |
| 7 | 5.26 % | | |
| 8 | 10.49 % | | |
| Total | 100 % | | 100 % |

TABLE V. PERCENTAGE OF EACH CLASS FOR WOUND ASSESSMENT

| Image | Original Image | Proposed Method | Percentage *(%)* of each class |
|---|---|---|---|
| A1 |  |  | Class 1 =60.76%<br>Class 2 = 8.36%<br>Class 3 =17.68%<br>Class 4 =13.20% |
| A2 |  |  | Class 1 =61.83%<br>Class 2 = 0.55%<br>Class 3 =27.75%<br>Class 4 =9.87% |
| B1 |  |  | Class 1 =55.46%<br>Class 2 = 23.36%<br>Class 3 =2.87%<br>Class 4 =18.31% |
| B2 |  |  | Class 1 = 53.24%<br>Class 2 = 0%<br>Class 3 = 16.10%<br>Class 4 = 30.66% |

In Table V, A1 and B1 are pre-healing wounds while A2 and B2 are images after a period of healing. After healing, the proportion of red decreases while the proportion of pink increases. This shows appropriate recovery. K-means clustering would allow a doctor or specialist to assess the severity of the wound and to track recovery via a telemedicine system.

## V. CONCLUSION

This paper has presented a method for finding the optimal threshold value for image segmentation. We adjusted the traditional Otsu algorithm by incorporating

PSO. The performance of the two methods was compared by application to 50 images from Medetec. The proposed method was able to segment the image closer to the edge of the wound, while removing more of the background. This was possible when the wound and surrounding skin area were close in size to the background and the two were distinct in shade. It was also effective when the skin and wound were of very similar shade.

To assist assessment of wound severity, the K-mean method was used to extract the color features from the segmented image. The percentage change in shade before and after treatment could be derived. This will allow doctors to more accurately assess the severity of a wound via a telemedicine system. The choice of fitness function for evaluating the particles in PSO could benefit from further study.

## Conflict of Interest

The authors declare no conflict of interest.

## Author Contributions

Wanyok discussed the topic, provided guidance the overall research and edited the manuscript. Chontida, Jidapa and Pakorn executed the experiments and wrote the paper. All authors have approved the final version of the manuscript.

## References


[1] R. G. Frykberg and J. Banks, "Challenges in the treatment of chronic wounds," *Advances in Wound Care*, vol. 4, pp. 560-582, Sep. 2015.

[2] C. Chakraborty, "Computational approach for chronic wound tissue characterization," *Informatics in Medicine Unlocked*, vol. 17, 2019.

[3] R. Mukherjee, D. D. Manohar, D. K. Das, A. Achar, A. Mitra, and C. Chakraborty, "Automated tissue classification frame-work for reproducible chronic wound assessment," *BioMed Research International*, vol. 2014, pp. 1-9, June 2014.

[4] N. Otsu, "A threshold selection method from gray-level histograms," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 1, pp. 62-66, June 1979.

[5] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Proc. International Conference on Neural Networks*, vol. 4, pp. 1942-1948, 1995.

[6] D. Wang, D. Tan, and L. Liu, "Particle swarm optimization algorithm: An overview," *Soft Computing*, vol. 22, pp. 387-408, Sep. 2018.

[7] L. Jianzhuang, L. Wenqing, and T. Yupeng, "Automatic thresholding of gray-level pictures using two-dimension Otsu method," in *Proc. International Conference on Circuits and Systems*, June 1991, vol. 1, pp. 325-327.

[8] K. Wei, T. Zhang, X. Shen, and J. Liu, "An improved threshold selection algorithm based on particle swarm optimization for image segmentation," in *Proc. Third International Conference on Natural Computation*, April 2017, vol. 5, pp. 591-594.

[9] S. R. Dubey, P. Dixit, N. Singh, and J. P. Gupta, "Infected fruit part detection using K-means clustering segmentation technique," *International Journal of Interactive Multimedia and Artificial Intelligence*, vol. 2, pp. 65-72, June 2013.

[10] J. MacQueen, "Some methods for classification and analysis of multivariate observations," in *Proc. Fifth Berkeley Symposium on Mathematical Statistics and Probability*, 1967, vol. 1, pp. 281-297.

[11] R. Pemula and C. N. Raju, "The optimal thresholding technique for image segmentation using fuzzy Otsu method," *IAES International Journal of Artificial Intelligence*, vol. 4, pp. 81-88, Sep. 2015.

[12] C. Chakraborty, "Chronic wound image analysis by particle swarm optimization technique for tele-wound network," *Wireless Personal Communications*, vol. 96, pp. 3655-3671, April 2017.

[13] Y. Zhao, X. Yu, H. Wu, Y. Zhou, X. Sun, S. Yua, S. Yu, and H. Liu, "A fast 2-D Otsu lung tissue image segmentation algorithm based on improved PSO," *Microprocessors and Microsystems*, vol. 80, pp. 1-8, Feb. 2021.

[14] S. Lingeswari, P. M. Gomathi, and S. P. Kailasam, "A study of tomato fruit disease detection using RGB color thresholding and K-means clustering," *International Journal of Computer Science and Mobile Computing*, vol. 10, pp. 51-59, Aug. 2021.




**Wanyok Atisattapong** received the Ph.D. from Mahidol University, Thailand, in 2009. She currently works at the Department of Mathematics, Thammasat University. Wanyok does research in Artificial Intelligence and Data Mining. Her recent publication is 'Wang-Landau sampling for estimation of the reliability of physical networks'.