Hybrid Segmentation of Microcalcification in Mammogram Images by using Fractional Order Darwinian Particle Swarm Optimization and Mathematical Morphology Methods

Nurul Ain Suraya Rosli[1], Nurul Fatin Syazwany Baharuddin[2], Alia Natasha Norzain[3] and Aminah Abdul Malek[4*]

Faculty of Computer and Mathematical Science,
Universiti Teknologi MARA Cawangan Negeri Sembilan
70300 Seremban, Negeri Sembilan, Malaysia
[1]nurulainsuraya98@gmail.com,[2]fatinsyazwany41@gmail.com,[3]alianatasha1311@gmail.com,
[4]aminah6869@uitm.edu.my

(indicates the corresponding author)*

ABSTRACT

Image segmentation is a process of extracting desired area of microcalcification on mammogram images. In mammograms, microcalcification can be seen as early sign of breast cancer. The detection of microcalcification is difficult to be identified due to low contrast and existing noise between microcalcification and surrounding tissue. A technique that has been widely used in segmentation is Particle Swarm Optimization (PSO). However, a general problem with PSO and other optimization algorithms is to get stuck in an optimum local stage where it can do well on certain images but can fail on another. Thus, Fractional Order Darwinian Particle Swarm Optimization (FODPSO) is used to segment microcalcification and distinguish from the background tissue of mammogram images. In general, FODPSO has a high fitness value to generate an efficient segmentation, but there are still some images that come out with unwanted regions of microcalcification. Therefore, an improved version of the FODPSO by using the Mathematical Morphology (MM) method is conducted to enhance the segmentation results. Morphology involves theory of analyzing the shape and texture of the image. The role of MM is used to obtain smooth shape and remove unwanted pixels of microcalcification. The algorithms are tested on 30 mammogram images which consists of microcalcification. The performance of improved FODPSO is evaluated by measuring the accuracy and sensitivity of the segmentation result. The evaluation used the percentage relative error of area and compared the result between method and expert. The accuracy and sensitivity of the segmentation results are 93.30% and 83.33% respectively. Hence, it is proven that the improved FODPSO method has the ability to segment the microcalcification on mammogram images and it can give a future reference.

Keywords*: Fractional Order Darwinian Particle Swarm Optimization, Mathematical Morphology, Microcalcification, Mammogram Segmentation.*

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INTRODUCTION

Microcalcifications are small spots of calcium deposit and the scope of width is from 0.1 to 1 mm. They appear in mammogram as small groups of several pixels, including high-intensity and closed shapes relative to nearby pixels (Basile et al., 2019). According to Wilkinson et al. (2017), microcalcifications result from the accumulation of two forms of calcium well within the breast tissue which are calcium oxalate and calcium phosphate. Thus, image segmentation is required to remove the interest abnormality from the mammograms.

Segmentation applies to the way toward dividing the digital image into meaningful areas. In other words, image segmentation can categorize a label to each pixel in the image such that pixels with the same label share certain visual characteristics. These regions are more meaningful than individual pixels for further interpretation and analysis of the images (Ghamisi et al., 2011). Segmentation can be classified between edge based and region based. Edge based models use picture inclination to manage curve development, which generally touches noise and powerless edges. Region based typically execute better when image noise and weak object limits exist. Fractional Order Darwinian Particle Swarm Optimization (FODPSO) is a multilevel thresholding technique which falls under region based category (Wang et al., 2009). This approach uses fractional calculus to control the convergence rate. Thus, FODPSO method is used in segmenting the microcalcification. Hence, the result of FODPSO method is improved in post processing phase using Mathematical Morphology (MM) method.

Image post processing is defined as transforming an image into a form that is easier to interpret (Ledda, 2007). It is an essential process in order to obtain a smooth shape and fill in any holes in the region. Mathematical Morphology is a powerful image analysis technique which can be defined as a theory that provides a number of useful tools for image analysis of spatial structures. This theory is applied in image processing, shape analysis, coding and texture analysis (Ledda, 2007). Generally, MM is used for extracting image component to provide useful information. This information helps in representation and description of the interest object in the image. It is also used in structuring element and measuring the shape of an image. Thus, in this study, method of FODPSO and Mathematical Morphology are used in segmenting microcalcification in mammogram images.

HYBRID SEGMENTATION

Fractional Order Darwinian Particle Swarm Optimization

Fractional Order Darwinian Particle Swarm Optimization (FODPSO) is a method in image analysis that utilizes multilevel thresholding procedures. This method was introduced by Couceiro in 2011 and it is an augmentation of Darwinian Particle Swarm Optimization (DPSO) by using Fractional Calculus (FC) to control convergence rate. FODPSO originates from Particle Swarm Optimization (PSO), established in 1995 by Eberhart and Kennedy. This algorithm is inspired by the sociological conduct related to the flocking of birds.

PSO act as a fitness function to find the optimal solutions using a swarm of particles. Each particle updates its moving direction according to the best position itself *(Pbest*) and the best position of the whole population (*Gbest*) formulated as follows:

$$V_i(t+1) = \omega V_i(t) + c_1 r_1 (P_i - X_i t) + c_2 r_2 (P_g - X_i t) \tag{1}$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{2}$$

where V_i is the moving velocity, X_i is the particle position at iteration i, P_i denotes as cognition part called *Pbest* and P_g represents the social part called *Gbest*. ω, c, r denoted the inertia weight, learning factors and random numbers respectively.

DPSO runs several simultaneous parallel PSO algorithms to upgrades the PSO calculation's capacity to escape from nearby optima. DPSO algorithm spawns' particles or extends swarm life when the swarm gets better optimum. Otherwise, it deletes particles or reduces swarm life. DPSO has been proven to be superior to original PSO in preventing premature convergence to local optimum (Couceiro et al., 2012).

Fractional Order Particle Swarm Optimization (FOPSO) is a developed version of DPSO that introduces fractional calculus to model particles approach, which demonstrates a potential for controlling the convergence of algorithms. The discrete time implementation introduced by Grünwald-Letnikov is defined as follows (Ahilan et al., 2019):

$$D^{\alpha}[V(t)] = \frac{1}{T^{\alpha}} \sum_{k=0}^{r} \frac{(-1)^k \Gamma(\alpha+1) V(t-kT)}{\Gamma(k+1)\Gamma(\alpha-k+1)} \tag{3}$$

where T is the sampling period and r the order for truncation. To apply the fractional calculus, Equation (1) has been rewritten with $\omega = 1$, namely:

$$V_i(t+1) - V_i(t) = c_1 r_1 (P_i - X_i t) + c_2 r_2 (P_g - X_i t) \tag{4}$$

The left side $V_i(t+1) - V_i(t)$ is a discrete version of $D^{\alpha}[V(t)]$ with $\alpha = 1$. $D^{\alpha}[V(t)]$ denotes the derivative of velocity. Then, substitute Equation (3) into Equation (4) with $r = 4$, yielding the following equation:

$$\begin{aligned} V_i(t+1) = \alpha V_i t + \frac{1}{2}\alpha V_i(t-1) + \frac{1}{6}(1-\alpha)V_i(t-2) + \frac{1}{24}\alpha(1-\alpha)(2-\alpha)V_i(t-3) \\ + c_1 r_1 (P_i - X_i t) + c_2 r_2 (P_g - X_i t) \end{aligned} \tag{5}$$

Employ Equation (5) to update each particle's velocity in DPSO then generating a new algorithm named Fractional Order Darwinian Particle Swarm Optimization (FODPSO). Different value of α is to controls the convergence rate of the optimization process.

Mathematical Morphology

Mathematical Morphology (MM) is an image processing field focused on principles derived from set theory and lattice theory. For several years, MM simply called morphology has been used to process the binary images (Akram, 2019). The first morphological operation is an erosion which is the process of lessening the size of the objects. The outcome of the erosion operation on the binary image based on the selection of the basic shapes. The basic shape is the structuring element which is the line and it provides a possible match in the image. Thus, the erosion operation on binary image I using structuring element S can be expressed as follow:

$$I \ominus S = \{c \mid (S)_c \subseteq I\} \tag{6}$$

where $I \ominus S$ was defined as the erosion of I by S (Akram, 2019).

Meanwhile, the process of dilation can be defined in a set theory as below:

$$I \oplus S = \{c \mid c = i + s, i \in I, s \in S\} \tag{7}$$

where $I \oplus S$ represented as the dilation of I by S (Akram, 2019). In other terms, the opposite of the erosion which reduces the size of the object, the dilation comes out with the process of widening the foreground object. The definition highlighted the role of image shifting in the operation of dilation. The centre of the structuring element shifted to every bright pixel in the binary image. Thus, the result shows that the image grows its size according to the shape of the structuring element.

The opening process has similar to the erosion such as identifying certain areas that are similar to the form of the structuring element in the foreground region. However, compared to the simple erosion, the opening process retains more foreground area as it eliminates small details from the image.

Therefore, the opening operation can be defined as follow:

$$I \circ S = (I \ominus S) \oplus S \tag{8}$$

which erosion followed by dilation process (Akram, 2019). The dilation will tend to remove erosion operation, however objects that disappear due to the erosion will not be retrieved by the dilation process. Therefore, according to (Ledda, 2007), opening operation is a smoothing filter.

IMPLEMENTATION

The data were obtained from the National Cancer Society Malaysia (NCSM) in a standard size of mammogram images which consists of 30 mammography images. Then, the hybrid segmentation occurs in the second phase with Fractional Order Darwinian Particle Swarm Optimization. This focused to the segmenting of microcalcification and distinguishing from the background tissue of mammogram images. Next, an improved version of FODPSO by using Mathematical Morphology (MM) method is conducted to enhance the segmentation results.

The role of MM is used to obtain smooth shape and remove unwanted pixels of microcalcification. The most frequent morphological operations include erosion, dilatation, opening and closing. However, this study will brief about the erosion, dilatation and opening as it is the operators that have been used in the development of the post processing techniques.

RESULTS AND DISCUSSION

Segmentation Results of Hybrid Method

One of the objectives of this study is to segment microcalcification on mamography images using a hybrid method. The following figure illustrates the sample of results obtained.

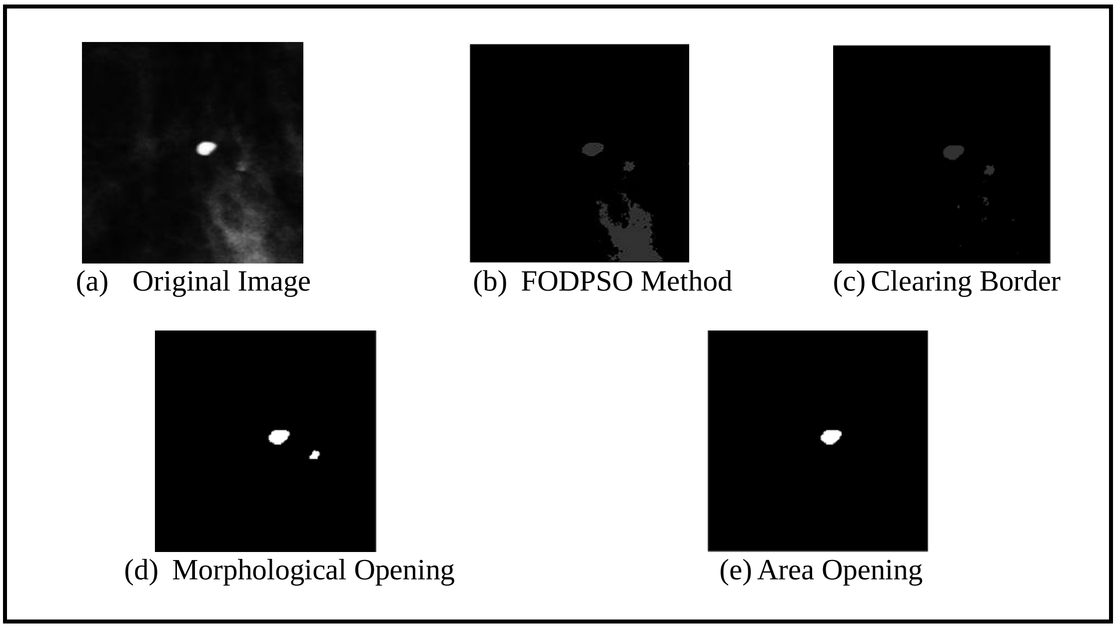

Figure 1. Segmentation Process of Hybrid Method

Image (a) shows the original image of microcalcification. The segmentation process using FODPSO method was depicted in Figure 1(b). However, this method considers the density of the breast as segmented region. Therefore, this problem was solved by reducing the overall intensity level and deleting lighter structures linked to the boundary of the picture, as shown in the image (c). next, the segmentation proceeds by performing a morphological opening. In this stage, a linear structuring element was chosen to eliminated the tiny details while retaining the structure and size of the requires objects in the image. As a result, the output changed from the grayscale to the binary images and it was portrayed on image (d). Unfortunately, image (d) illustrates some of the noise fragments were still present. In order to achieve the successful image of segmentation results, area opening operation was executed at this stage. All the connected components that have fewer than pixels from binary images were removed. Finally, image (e) was obtained as the final segmentation results. Figure 2 shows three samples of segmentation results by using the FODPSO method.

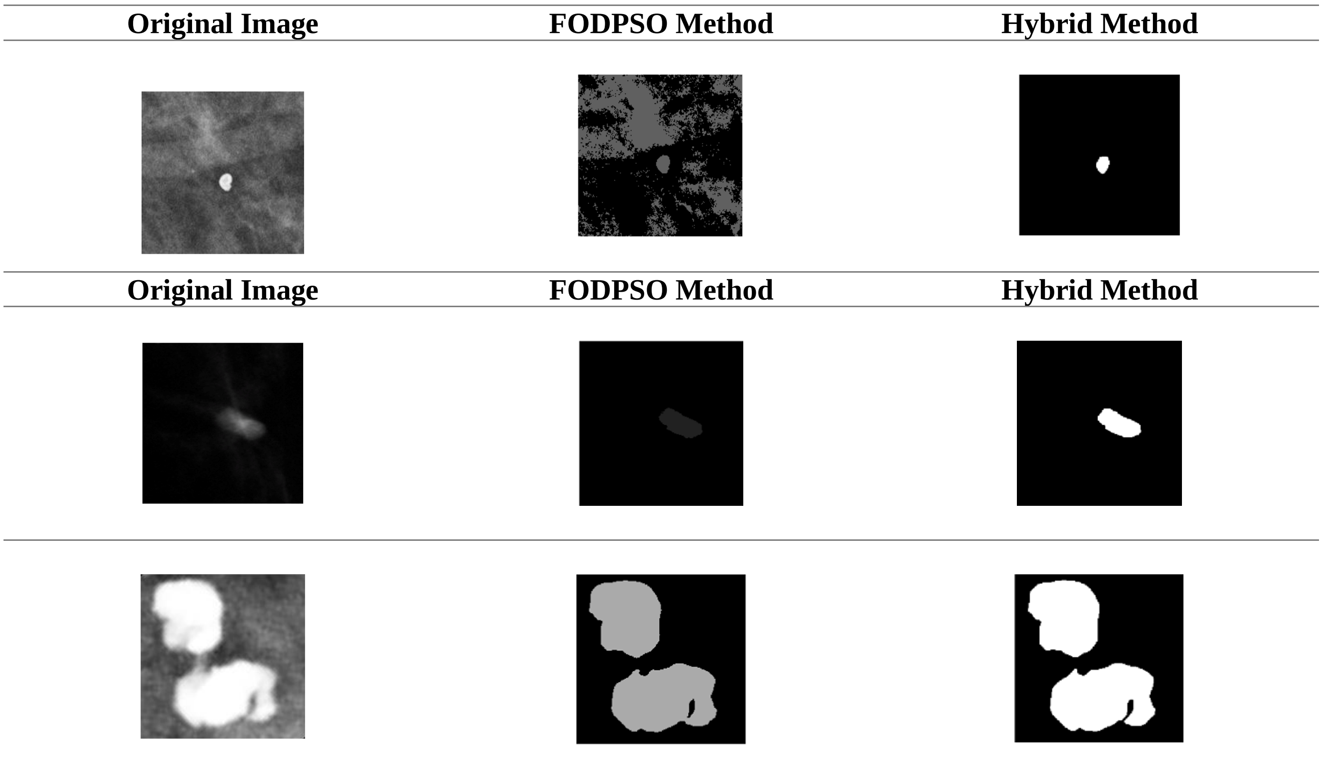

Figure 2. Comparison Segmentation Result using FODPSO and Hybrid

Figure 2 shows that the hybrid method successfully segmented the microcalcification even though there is a different size of intensity values and the original images are quite blurry compared to other images. In addition, the proposed method was capable of segmenting the clustered microcalcification. However, to achieve successful segmentation results, there are some parameters that need to be set manually according to the images.

Table 1. Optimal Parameters Value Used in FODPSO Method

Parameter	Optimal Value
α	0.6
c_1	0.8
c_2	0.8
w	1
Number of swarms	4

A faster optimization convergence is obtained from a fractional coefficient α in the range [0.5, 0.8] in most circumstances. Hence, this study chose 0.6 as a fractional coefficient. Besides, the population size is very crucial to be optimized in order to get overall good solutions in an acceptable time. Number of swarms that have been used in this experiment is 4. Next, the inertia weight w is adapted over the PSO iterations. This parameter's high starting value encourages diversification (exploration). Intensification (exploitation) favours the reduction of this value. Typically used in metaheuristics, this approach enables the results to be optimised by controlling the balance between exploration and exploitation of the search space (Mekhmoukh & Mokrani, 2018). Moreover, the higher the inertia weight w, gives the better results with fast convergence rate and aggressive motion towards the suggestion area (Singh & Singh, 2013). Hence, the inertia weight is set into 1 as the optimum values while the individual and global weights are set up into $c_1 = c_2 = 0.8$. In conclusion, parameter values are selected in such a way that faster convergence takes place.

Generally, the pattern of structuring elements was crucial as the precise information could be received by selecting appropriate structuring features. Thus, in this study linear was chosen to be structuring element and it consists of two parameters. The parameters that were presented are l and d which has different values for each image. The l is defined as length of a linear structuring element in the strel function and it was formed as a positive number. To be more precise, it expresses the length between the centres of the structuring element members at the opposite end of the data. Meanwhile, d specifies the angle (in degree) as calculated in the counter-clockwise direction from the horizontal axis. In addition, the maximum number of pixels were set up as a parameter in area opening to eliminate all related components with less than the pixels from the binary images. The most frequent values of length and degree are 5 and 70 respectively, while the pixel numbers that were mostly used are 100.

Performance Results of Hybrid Method

The performance of hybrid segmentation is measured by using accuracy and sensitivity. The accuracy and sensitivity are determined based on percentage relative error of area between the hybrid method and radiologists.

a) *Accuracy*: The accuracy was determined by the closeness of the hybrid segmentation and radiologists' results. It can be calculated by using the following equation:

$$Accuracy(\%) = 100 - \left(\frac{\sum_{n=1}^{30} PRE}{30} \right) \tag{9}$$

where $\sum_{n=1}^{30} PRE$ is denoted as the sum of percentage relative error of all 30 mammography images. Thus, Figure 3 shows the histogram that elucidates the comparison of average area of hybrid segmentation results and segmented by radiologists.

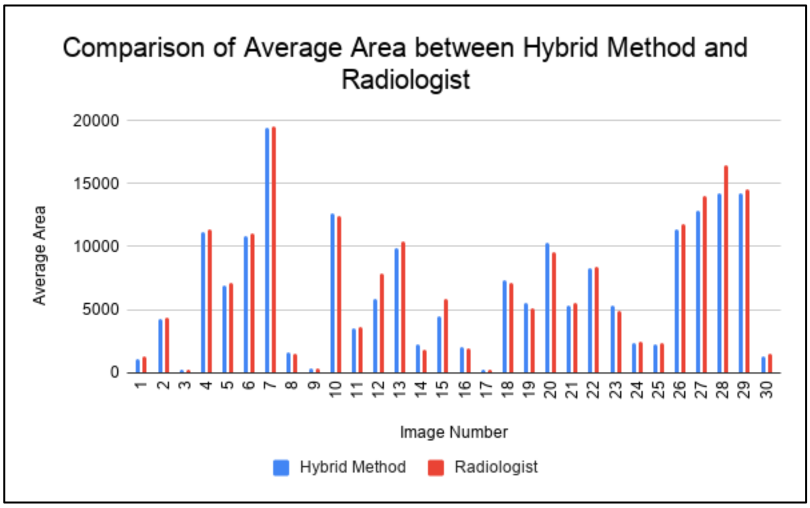

Figure 3. Average Area of Hybrid Method and Expert

Based on Figure 3, there was only slight difference between the hybrid method and expert findings. The average percentage error calculated was only 6.7% which leads to 93.3% accuracy. Hence, it can be concluded that this hybrid method can be considered accurately segmented based on the average percentage error obtained.

b) *Sensitivity*: Sensitivity was used to analyse the performance of the hybrid method using following equation:

$$Sensitivity(\%) = \frac{TP}{TP + FN} \times 100\% \tag{10}$$

where TP is the true positive and FN is the false negative. The true positives (TP) were obtained by the frequency of the images measured by the recognition statistic on the specific range of each image based on the percentage relative error as in Table 2. TP is graded as very good, good and average.

Table 2. The Recognition Statistic of Segmentation

Recognition Statistic	**Range of Percentage Relative Error (%)**
Very Good	[0,5)
Good	[5,10)
Average	[10,15)
Below Average	[15,20)
Poor	20

The range of percentage relative error from 0 to 5 percent indicates 'very good' statistics. For 'good' and 'average' classification of recognition, the segmentation region has the percentage of relative error range 5 to 10 and 10 to 15 percent. Meanwhile, 'below average' is 15 to 20 percent relative error. More than 20 percent would be referred to as 'poor' recognition statistic.

Based on Table 2, the hybrid segmentation method has the sensitivity of 83.3% which can be inferred as good in segmenting the region of interest with high sensitivity rate. Thus, it shows that the proposed hybrid methos is efficacious in segmenting microcalcifications.

CONCLUSION

The hybrid method is an improvisation of the original FODPSO method and Mathematical Morphological method in order to remove noise and smoothened the images by using the morphological opening. Therefore, the results of the region area will be clearer and easier to evaluate. The experimental results produced excellent performances with 93.30% for accuracy and 83.33% for sensitivity results. The proposed method therefore has demonstrated its authenticity for successfully segmenting the microcalcification images.

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