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OPTIMIZATION OF FUZZY C-MEANS CLUSTERING USING PARTICLE SWARM OPTIMIZATION IN BRAIN TUMOR IMAGE SEGMENTATION

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ABSTRACT

Tumor is an abnormal cell development in the body, one of them in the brain. Before performing examine of brain tumor patients, medical team will first analyze the results of medical imaging to find out the part that is a tumor and not the tumor in the medical image. Analysis of tumor segmentation that is still manually requires a longer time, thus inhibiting the treatment process of patients to enter the next treatment stage and delay the latest information about the health of patients. Therefore, a mechanism is needed to automatically segment brain tumor regions. Until now, a lot of research has been done to segment brain tumor regions automatically. Based on research conducted by previous researchers about the segmentation of brain tumor regions, some researchers still use segmentation algorithms that are sensitive to initial position of the cluster center or determining seed points which often contain either too many regions. There is a possibility of getting unfavorable segmentation result. This research aims to propose method to develop an existing partition-based brain tumor segmentation algorithm by adding stages of optimization algorithm of the image segmentation algorithm. In this research, image segmentation algorithm used is Fuzzy C-Means. For optimize Fuzzy C-Means, used Particle Swarm Optimization. Optimization algorithm run concurrently with segmentation algorithm. The performance measurements used by comparing objective function of original algorithm without optimization with 6 images data. As a result, objective function of Fuzzy C-Means optimized by Particle Swarm Optimization (FCM - PSO) achieve more minimum than original Fuzzy C-Means (FCM) of six images data. It means, objective function of Fuzzy C-Means optimized by Particle Swarm Optimization closer to global minimum and can used to optimize segmentation algorithm.

Keywords: *Optimization, Segmentation, Fuzzy C-Means, Particle Swarm Optimization, Brain Tumor*

1. INTRODUCTION

Cancer is one of the leading causes of death in the world. Cancer is an abnormal and uncontrolled cell development in the body. Cancer is a tumor that has entered the malignant phase of tumor cells that have grown and spread to other parts, while tumors in the benign phase are tumor cells that have not spread to other normal parts of the body [1]. Until 2017, there were more than 688 thousand people with brain tumors and central nervous systems in the United States consisting of 138 thousand people suffering from malignant tumors or cancer and 550 thousand people suffering from benign tumors [2]. In Indonesia, according to Dr. Agus C. Anab, per year, the number of patients with brain tumors continues to increase, which penetrates 25 thousand patients [3]. The odds ratios of tumors and cancers of the eyes, brain and central nervous system in 2011 had a prevalence percentage of 4.6% and were ranked 7th out of 12 types of tumors and cancers that occurred in Indonesia [4].

Patients suspected of having a brain tumor will usually undergo several examination procedures by the hospital. One of the stages of the examination is examining the tumor using a medical imaging device. When examining brain tumors using medical imaging devices, Radiologists usually use two types of medical imaging devices, namely Magnetic Resonance Imaging or MRI and Computed Tomography or CT [5]. MRI uses radio waves and strong magnets to produce images. Gadolinium can be injected into a blood vessel before scanning to help improve image details for the better. CT uses x-rays to create cross-sectional images of the brain and spinal cord (or other parts of the body). Unlike ordinary x-rays, CT produces more detailed images of soft tissue in the body. However, MRI is better at viewing the brain and spinal cord and is considered the best imaging tool for seeing tumors in the brain area because MRI produces more detailed images than those from CT. However, CT shows better details of bone structure near the tumor. There are several variations of MRI imaging techniques, namely T1, T2, FLAIR, and others [6]. MRI T2 has the advantage of displaying damaged brain tissue more clearly and brighter. Researchers usually choose MRI tool to conduct a research

Before performing examine of brain tumor patients, medical team will first analyze the results of medical imaging to find out the part that is a tumor and not the tumor in the medical image. However, the analysis is still manual or still depends on expertise. The problems may arise in the process of examination of the patient with the help of medical imaging is error analysis in determining the area of the tumor and not a tumor on the results of medical images that are prone to error to diagnosis a patient's health and are vulnerable to the difference interpretation between one doctor and another doctor on the results of the medical image [7]. Analysis of tumor segmentation that is still manually requires a longer time, thus inhibiting the treatment process of patients to enter the next treatment stage and delay the latest information about the health of patients. Therefore, a mechanism is needed to automatically segment brain tumor regions.

2. LITERATURE REVIEW

Until now, lot of research has been done to segment brain tumor regions automatically. Some research use Image Processing and Artificial Intelligence as a tools. Zhe Xiao, et al [8] conducted a research to segment brain tumor regions using Deep Learning based algorithms, namely Stacked Denoising Auto Encoder (SDAE). However, like other Deep Learning based algorithms, a parameter such as number of layers is needed in the training process. The number of layers in this research was determined by trial and error and random to get the best results. This is very time-consuming and require extensive computational to determine the right hyperparameter value and susceptible to overfitting and trapped to local optimum, a situation where the training process produces good accuracy, but produces poor accuracy in the testing process because the model formed only memorizes training data, not generalizes training data.

Research for segmenting region of the brain tumor is also done by Nerurkar [9] using Region Growing algorithm. However, the Region Growing algorithm works depending on the seed point specified by the user. The role of the user in the method proposed in this study is very high because if the user is not right in determining the seed point and its growth criteria, the tumor area is not perfectly segmented. Moreover, region growing often ends in a local optimum of region labeling, the global optimum is not found because of the character of the optimization [10].

Sharmila and Joseph [11] also conducted research to determine whether an MRI image of the brain is a brain that is identified as normal brain or brain with tumor. This research uses Support Vector Machine and Naïve Bayes Classifier to classify into two groups of image classes, namely the brain with normal tumors and brains. Before carrying out the training process, the image features are extracted only in the tumor area. To find out whether there are tumors in the brain image, K-Means algorithm is used to segment tumor region. However, the K-Means algorithm is required to initialize the initial cluster centers randomly so no guarantee whether the initial cluster centers are initialized an initial cluster centers are the best and the tumor region segmentation results are prone to be inaccurate.

The similar method of segmentation of tumor regions has also been done by Pandey, et al [12]. This research segmented brain tumor regions using the Fuzzy C-Means algorithm. Fuzzy C-Means works almost the same as K-Means because it is still in one category, namely partition-based segmentation algorithm, but Fuzzy C-Means is not absolutely categorizing a point into a cluster and calculating membership functions for each cluster. However, same with the K-Means algorithm, initialization initial cluster centers are still to be determined randomly so it does not guarantee the result of a perfect segmentation tumor region. The partitioning methods such as K-Means and Fuzzy C-Means, they are sensitive to initial clustering center and different clustering centers largely influences the clustering result, they are also prone to be trapped in local minimum [13].

Based on research conducted by previous researchers about the segmentation of brain tumor regions, some researchers still use segmentation algorithms that are sensitive to initial position of the cluster center in the K-Means algorithm and Fuzzy C-Means or determination by trial and error such as determining seed points in the Region Growing algorithm which often contain either too many regions (under-growing) or too few regions (over-growing) as a result of non-optimal parameter setting, still need post processing algorithm and randomly determine the number of layers and initial weights in Deep Learning based algorithm. Determination of cluster center randomly, or trial and error is certainly not optimal and vulnerable to imperfect segmentation results if there is no expert knowledge and will require time in conducting experiments to obtain perfect segmentation result. For this reason to overcome these weaknesses, an optimization algorithm is needed to optimize the process in the segmentation algorithm used to get the best results.

All previous research has established that optimization techniques have succeeded in overcoming clustering weaknesses [14]. Also, as described in section 1, one of the stages of diagnosis of brain tumors is to detect the presence of tumor areas in the brain and to segment the tumor area. The segmentation is the initial stage which aims to determine the location, shape, and even the type and severity of the tumor. In addition, as there are weaknesses in the segmentation algorithm that has been successfully applied previously for brain tumor segmentation. However, its main drawback should make the process still need post processing algorithm which may take longer. This is certainly not optimal and there is a possibility of getting unfavorable segmentation results. Therefore, there is additional stages in the process of brain tumor segmentation, optimize the objective function of the segmentation algorithm. Objective function in here is function that can be optimized by finding the highest or lowest value among all best possible values of the function. Optimize objective function in clustering means that the clustering will produce better cluster. Additional stage is running in one package and with the main algorithm so no manual additional post processing. Thus, the formulation of the problem in this research is how to optimize objective function of Fuzzy C-Means Algorithm as segmentation algorithm using Particle Swarm Optimization algorithm as optimization algorithm. Optimization using Particle Swarm Optimization in this research is quite simple because no need layers and neurons so the process is more lighten the system when running this algorithm and the time is quite short when running this algorithm until finish compared with previous research. Therefore, this research propose a method to optimize image segmentation algorithm and develop an existing partition-based brain tumor segmentation algorithm by adding stages of optimization algorithm of the image segmentation algorithm. With the proposed method, result from image segmentation algorithm will be more accurate and close with global minimum or condition where objective function value can be more minimum than objective function in local minimum condition towards same population data so medical team can give decision correctly to patient due to their condition.

Research related to brain tumor has reached the stage of identifying types of brain tumors using many algorithms. In this research, focused to develop existing brain tumor image segmentation research with adding method to optimize segmentation algorithm. The result only show objective function value from optimized algorithm and the result also compared with non-optimized segmentation algorithm. The test image used is the MRI T2 image totaling 6 images. Implementation is done using MATLAB 2018a. The performance measurements use objective function value resulting from proposed algorithm where in segmentation or clustering context, the lower value of the objective function, better the performance. In addition, this research also compared to non-optimized algorithm to show the most minimum objective function value between optimized and non-optimized result. This research has the usability, usefulness both scientifically and technologically. The scientific use of this research is in the form of developing partition-based segmentation algorithms that are hybridized with optimization algorithms. Technologically, the algorithm that has been developed and also implemented using the MATLAB 2018b program to produce minimum value objective function of segmentation algorithm.

3. THEORETICAL PARADIGM

This section explain basic theory used in proposed methodology, specifically about digital image, clustering, and optimization based on books.

3.1 Digital Image

Image can be defined as a 2D function, f (x, y), with : [15]

- *x* and *y* are spatial coordinates
- The amplitude *f* on the pair of coordinates (x, y) called the intensity or gray level of the image at that point

An image can be represented as a matrix. If *x*, *y* and *f* are all finite, and their values are discrete, they are called digital image. The digital image is composed

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of a finite number of elements, each having a specific location and value or intensity. These elements are called picture elements, image elements, pels, and also pixels. The field of digital image processing refers to the processing of digital image using digital computers. A digital image that can be processed covers almost the entire spectrum of electromagnetic waves, ranging from gamma rays to radio waves.

From the visual content, the image can be divided into : [16]

- True Color Image

  True color image is an image that visually contains the color information, which is represented in the color pixel values component containing luminance, hue, and chrominance / saturation. Luminance is a measure of the brightness of a color. Increasing or decreasing the value of luminance means making the color brighter or darker. Hue is one of the main properties of color that is represented in the degree value (0 ° -360 °). Chrominance or Saturation represents the height of the low white light content in a color. The lower the value of chrominance (close to 0) then the color is getting pale (white) to be white or gray color and vice versa.

  Each point or pixel in the colored image has three color components R, G, and B are each generally encoded with 8 bits or a total of three 3 x 8 = 24 bits. Thus, a color image can contain as much as 224 color variations (16,777,216 color variations). Mathematically, the colored image is represented in the three dimensional matrix function f (n, m, k). Here n = {1, 2, 3, ..., N}, N is the number of rows, m = {1, 2, 3, ..., M}, M is the number of columns representing the pixel coordinate position, whereas the dimension k = {1,2,3} represents the red color component (1 = R), green (2 = G), and blue (3 = B).

- Gray Level Image

  Gray-level Image is an image in which the pixel value is represented only by the luminance value, which is generally encoded in 8 bits or means having a gray scale that varies from 0 to 255 (28 -1). The value represents the black color and the value 255 represents a gray color that varies from black to bright to white. Gray-level images can be obtained from color images through transformations from RGB color space to other color space (HSV, HSL, Lab, YCbCr or HCL). The Y, V, L components of the color space represent the gray-level image in question.

- Binary Image

  Binary image is part of a grayscale image that has only two gray levels, 0 for black and 1 for white, so each pixel of a binary image is encoded using only 1 bit. Binary image is calculated using threshold. If the pixel value is smaller than the threshold, the value is changed to 0 or black, and if it is greater than or equal to the threshold value then the value is changed to 1 or white.

3.2 Clustering

Clustering [17] is the process of partitioning a set of data objects (or observations) into subsets. Each subset is a cluster, such that objects in a cluster are similar to one another, yet dissimilar to objects in other clusters. The set of clusters resulting from a cluster analysis can be referred to as a clustering. Because a cluster is a collection of data objects that are similar to one another within the cluster and dissimilar to objects in other clusters, a cluster of data objects can be treated as an implicit class. In this sense, clustering is sometimes called automatic classification. Again, a critical difference here is that clustering can automatically find the groupings. This is a distinct advantage of cluster analysis. Clustering is known as unsupervised learning because the class label information is not present. For this reason, clustering is a form of learning by observation, rather than learning by examples.

There are many clustering algorithms in the literature. It is difficult to provide a crisp categorization of clustering methods because these categories may overlap so that a method may have features from several categories. Nevertheless, it is useful to present a relatively organized picture of clustering methods. In general, the major fundamental clustering methods can be classified into the following categories : [17]

- Partitioning methods

  Given a set of n objects, a partitioning method constructs k partitions of the data, where each partition represents a cluster and $k \leq n$. That is, it divides the data into k groups such that each group must contain at least one object. In other words, partitioning methods conduct one-

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level partitioning on data sets. The basic partitioning methods typically adopt exclusive cluster separation. That is, each object must belong to exactly one group. This requirement may be relaxed, for example, in fuzzy partitioning techniques.

- Hierarchical methods

  A hierarchical method creates a hierarchical decomposition of the given set of data objects. A hierarchical method can be classified as being either agglomerative or divisive, based on how the hierarchical decomposition is formed. The agglomerative approach, also called the bottom-up approach, starts with each object forming a separate group. It successively merges the objects or groups close to one another, until all the groups are merged into one (the topmost level of the hierarchy), or a termination condition holds. The divisive approach, also called the top-down approach, starts with all the objects in the same cluster. In each successive iteration, a cluster is split into smaller clusters, until eventually each object is in one cluster, or a termination condition holds.

- Density-based methods

  Most partitioning methods cluster objects based on the distance between objects. Such methods can find only spherical-shaped clusters and encounter difficulty in discovering clusters of arbitrary shapes. Other clustering methods have been developed based on the notion of density. Their general idea is to continue growing a given cluster as long as the density (number of objects or data points) in the "neighborhood" exceeds some threshold. For example, for each data point within a given cluster, the neighborhood of a given radius has to contain at least a minimum number of points. Such a method can be used to filter out noise or outliers and discover clusters of arbitrary shape.

- Grid-based methods

  Grid-based methods quantize the object space into a finite number of cells that form a grid structure. All the clustering operations are performed on the grid structure (i.e., on the quantized space). The main advantage of this approach is its fast processing time, which is typically independent of the number of data objects and dependent only on the number of cells in each dimension in the quantized space.

3.3 Optimization

Global optimization [18] is the branch of applied mathematics and numerical analysis that focuses on optimization. Global optimization is about finding the best possible solutions for given problems. The goal of global optimization is to find the best possible elements $x^\star$ from a set X according to a set of criteria F = *{f1, f2, .., fn}*. These criteria are expressed as mathematical functions, the so-called objective functions.

Generally, optimization algorithms [18] can be divided in two basic classes: deterministic and probabilistic algorithms. Deterministic algorithms are most often used if a clear relation between the characteristics of the possible solutions and their utility for a given problem exists. Then, the search space can efficiently be explored using for example a divide and conquer. If the relation between a solution candidate and its "fitness" are not so obvious or too complicated, or the dimensionality of the search space is very high, it becomes harder to solve a problem deterministically. Then, probabilistic algorithms come into play. The initial work in this area which now has become one of most important research fields in optimization was started about 55 years ago. An especially relevant family of probabilistic algorithms are the Monte Carlo-based approaches. They trade in guaranteed correctness of the solution for a shorter runtime. This does not mean that the results obtained using them are incorrect– they may just not be the global optima.

4. PROPOSED METHODOLOGY

Broadly speaking, this research using MRI T2 image of a grayscale brain tumor. Then, the particle as representation for initial cluster and its value are generated randomly for the first iteration. Thus, initial fitness Fuzzy C-Means function can be calculated using initialized each particle towards intensity pixel image. After that, evaluate the fitness function in Particle Swarm Optimization algorithm by calculate updated particle and fitness function repeatedly until meet stopping criteria. When the iteration stop, the minimum value of the fitness function is obtained. So in this research the stopping criteria is number of iteration. Therefore this research show increment iteration of every experiment to know the change in the value of objective function whether the change is large or relatively small because it has reached the lowest

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objective function value or even the minimum global value. The research method is presented on the flowchart in figure 1.

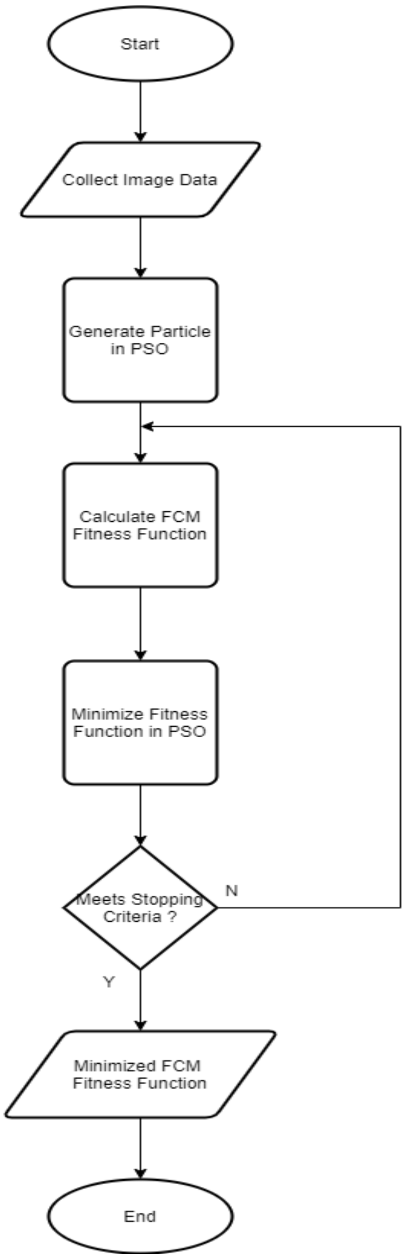

Figure 1 : Flowchart of Proposed Methodology

4.1 Image Data Collection

The data used in this research are the axial brain tumor image of MRI T2. MRI T2 image data taken from Pelni Hospital, Slipi, West Jakarta, Indonesia. The number of images are 21 but the images originated from one same patient. The images have 512x512 pixels grayscale in PNG format. In this research, only use 6 images as sample image because the tumor looks clear and easily distinguished between tumor region and non-tumor region on that sample. This research don't have training images due to segmentation algorithm used is clustering or unsupervised learning which works on only testing images. The sample of images data presented on figure 2.

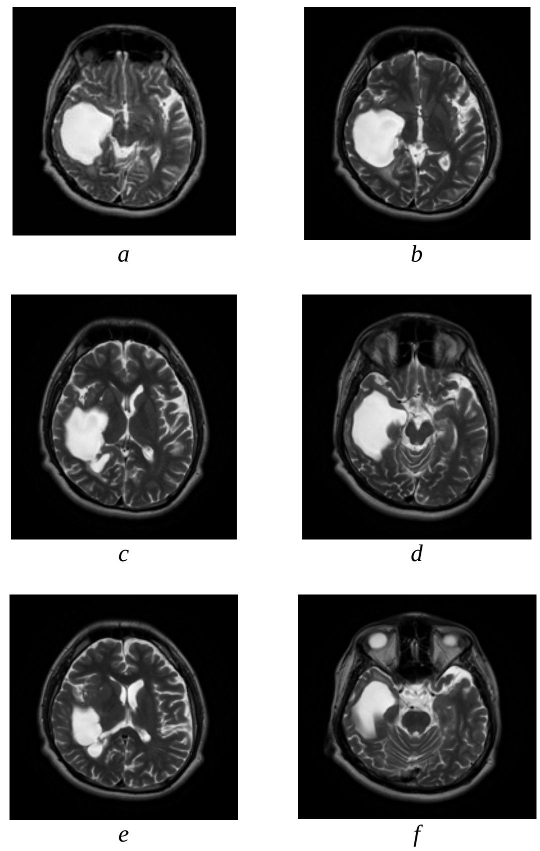

Figure 2 : Example of Brain Tumor Image used in this Research

4.2 Generate Particle in Particle Swarm Optimization

Particle Swarm Optimization (PSO) has been proven to successfully improve the performance of machine learning methods and easy to implement because PSO does not have many procedures such as selection, mutation or crossover [14]. Initialize particle is the first step in this method. Before initialize particle, needed to determine parameter in Particle Swarm Optimization. Parameters which needed are number of iteration, number of cluster, number of particle, learning rate for cognition component, learning rate for social component, and cognition component. Number of cluster used are 2 clusters because in this research, brain have two parts, tumor part and non-tumor part. In general,

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effective value of learning rate for cognition component and learning rate for social component is 2, thus, this research use 2 as learning rate for cognition component and learning rate for social component. Besides that, the effective number of particles are 30, because that number is produce the result that nearly optimum global and quite small for time complexity and number of particle don't give impact to optimum solution, but just give impact to speed of process [19].

Initialization of each particle is done using random number generator. Result of random number generator is assign to empty array of each particle as initial cluster position towards Fuzzy C-Means. Because the image segment into 2 cluster, tumor and non-tumor part, then each particle has two clusters of cluster positions. Then all intensity pixels on all image which want to segment into 2 cluster, assigned to each particles and each particle have different cluster position which in this research, cluster position is intensity. So, all intensity pixels on image and initial cluster center has been represented to each particles. Besides that, value that initialized randomly is also current particle position. Flowchart of initialization and generation of each particle presented in figure 3

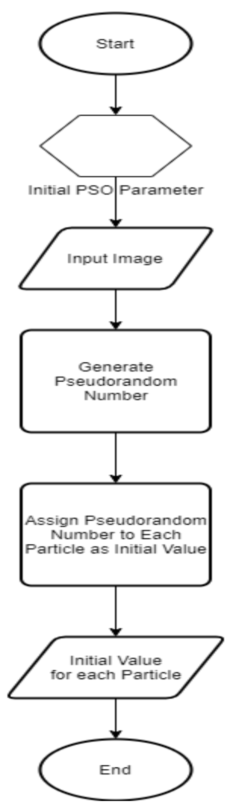

Figure 3 : Flowchart of Generate Particle in Particle Swarm Optimization

4.3 Calculate Fitness Fuzzy C-Means Function

After the initial value of each particle is initialized, each particle is measured based on a fitness value. This function takes the parameters of an each particle and produces the fitness value output of each particle. So, fitness function is just representative of objective function in every particle. Calculate the fitness function using Fuzzy C-Means objective function for each particle that stated in equation calculate the fitness function using Fuzzy C-Means objective function that stated in equation 1 [14]

$$F(P) = \frac{1}{J_{FCM}} \quad (1)$$

J_{FCM} is objective function of Fuzzy C-Means stated in equation 2 [14].

$$(U, V) = \sum_{k=1}^{n} \sum_{i=1}^{c} (\mu_{ik})^m (d_{ik})^2 \quad (2)$$

Where U = μ_{ik} is a membership degree matrix with dimensions *c* x *n*, μ_{ik} is the degree of membership between *a* data *k* to group *i*. Membership degree (*m*) values are in the range 0 and 1. The higher the value of μ_{ik}, the greater the ownership of data *k* against the group *i*, $d_{ik} = |x_k - v_i|$ is the Euclidean distance between k and the center of the cluster *i*, m is a fuzzy index which has a value in the range | 1, ∞ | [14]. Objective function of Fuzzy C-Means becomes the benchmark of how minimum to be obtained. Each particle initialized represent different initial cluster center in Fuzzy C-Means. Initial cluster of Fuzzy C-Means calculated in equation 3 [14].

$$v_i = \frac{\sum_{k=1}^{n} (\mu_{ik})^m x_k}{\sum_{k=1}^{n} (\mu_{ik})^m} \quad (3)$$

Because in this research number of particles are 30, thus those 30 particle must be calculated of Fitness Function then each particle have different fitness function value. Before calculate fitness function of Fuzzy C-means, membership function have to calculated first because Fuzzy C-Means does not cluster absolutely any intensity pixels to a cluster, but all intensity pixels belong to all clusters with a certain membership value. Membership function of Fuzzy C-Means stated in equation 4 [14].

$$\mu_{ik} = \frac{1}{\sum_{k=1}^{n} \left(\frac{d_{ik}}{d_{jk}}\right)^{\frac{2}{m-1}}} \quad (4)$$

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Next, the value of initial cluster center and membership function is used to calculate fitness function of Fuzzy C-Means. Flowchart of calculate fitness function in Fuzzy F-Means formula presented in figure 4.

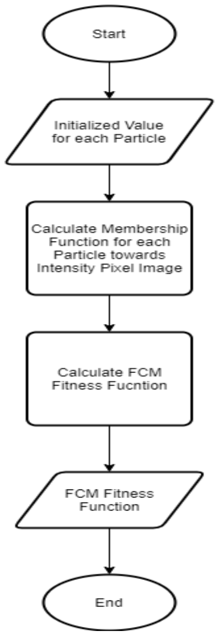

Figure 4 : Flowchart of Calculate Fitness Function Fuzzy C-Means Formula

4.4 Minimize Fitness Function in Particle Swarm Optimization

In fuzzy clustering algorithm, the goal is to minimize the objective function due to grouping the data points in a multi-attribute datasets to maximize the similarity within the same cluster and minimize the similarity between two different clusters [20], hence after get initial position and fitness function each particle, minimize the fitness function from FCM objective function using new particle position. To update particle position value, needed calculate particle velocity value. Calculation of particle velocity involve PSO parameter value that has been initialized before such as learning rate for cognition component and learning rate for social component and value that calculated before such as current particle position and best particle position amongst particle initialized or global best position. Definition of 'best' here is a particle that has the smallest fitness value amongst other particle. Then, after get particle velocity value, updated particle position value obtained from current particle position added with particle velocity value. Formula of particle velocity and updated particle position show in equations 5 and 6 [14].

$$V_i(t+1) = \omega V_i(t) + c_1 r_1 (P_i - X_i) + c_2 r_2 (P_g - X_i) \quad (5)$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \quad (6)$$

Pi is the best position for each particle and *Pg* is the best position for the swarm, r1 and r2 are random numbers with intervals [0,1], c1 and c2 are learning factors which represent a cognitive component and a social component respectively. The parameter t is an iteration index, ω is the inertia weight parameter used to balance global search capabilities and local search. Flowchart of minimize fitness function in Particle Swarm Optimization presented in figure 5.

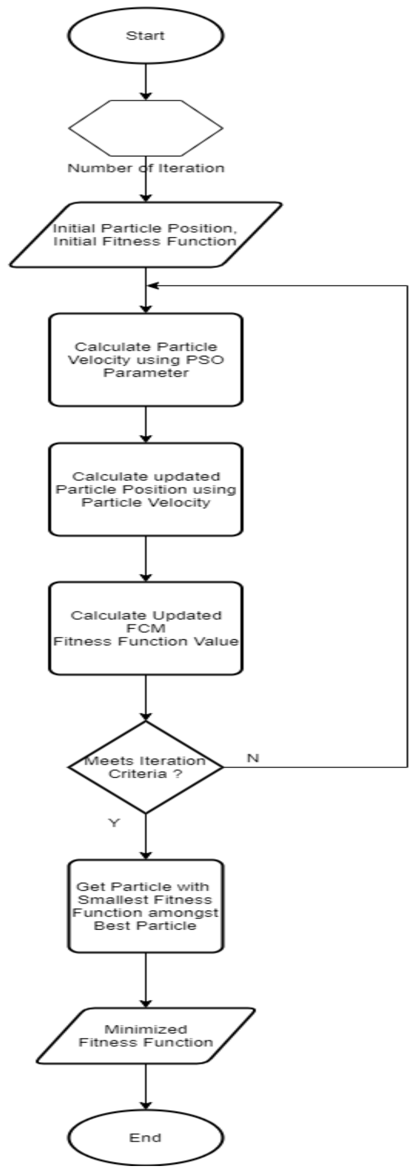

Figure 5 : Flowchart of Minimize Fitness Function FCM

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When the updated value of position each particle is obtained, calculate new fitness value of FCM using same formula with section 4.3. Then compare new fitness value with previous fitness value for each particle to get best fitness in each particle. Next, get new global best particle amongst best fitness particle in swarm. Then, calculate particle velocity again using new global best position fitness value and updated particle position, then calculate new particle position using particle velocity and calculate new fitness value each particle until meet stopping criteria, iteration. When meet stopping criteria, particle which have smallest fitness function amongst the best particle in swarm or new global best is taken as optimum solution for objective function of Fuzzy C-Means.

5. RESULT AND DISCUSSION

In this section describes the result of the proposed method. Result with proposed method also compared with original algorithm which not have optimization stage. Implementation of the both method and image data in the program is done using a notebook with an Intel Core i7 8th Gen processor, 32 GB RAM memory and MATLAB version 9.5.0 (2018b). Iteration used in both method for one images data from 10 to 50 iterations. The result shows comparison between proposed method, Fuzzy C-Means optimized by Particle Swarm Optimization (FCM - PSO) and original Fuzzy C-Means (FCM) without added any optimization algorithm. The value compared is Objective Function FCM and Objective Function FCM that has been optimized in fitness function FCM – PSO. The comparison using same computer notebook and same sample images when running FCM - PSO algorithm but because in this research initialization of each particle is done using random number generator so there is probability the result of objective function is different in every running. Table 1-6 show result of FCM (Fuzzy C-Means) optimized by PSO (Particle Swarm Optimization) and comparison with FCM (Fuzzy C-Means) original algorithm for 6 images.

Table 1 : Comparison between FCM and PSO - FCM for each iteration using Image Data 2(a)

Iteration	Objective Function	
	FCM	FCM - PSO
10	239167803.785182	$1.801448 \times 10^{-[illegible]}$
20	238675494.641140	$1.818442 \times 10^{-[illegible]}$
30	238675494.639058	$1.778227 \times 10^{-[illegible]}$
40	238675494.639058	$1.784128 \times 10^{-[illegible]}$
50	238675494.639058	$1.769248 \times 10^{-[illegible]}$

Based on table 1, in general FCM – PSO can achieve more minimum value of objective function than FCM in each iteration. More specifically, the minimum value of FCM objective function is in 30th iteration while FCM – PSO in 50th iteration just achieve minimum value although in the next iteration until final iteration, the minimum value of FCM objective function still same with 40th and 50th iteration. Thus, FCM has saturation point in 30th iteration different with FCM – PSO which have probabilities to increase or decrease in any iteration point.

Table 2 : Comparison between FCM and PSO - FCM for each iteration using Image Data 2(b)

Iteration	Objective Function	
	FCM	FCM - PSO
10	258003547.071975	$1.802080 \times 10^{-[illegible]}$
20	242409851.310870	$1.778048 \times 10^{-[illegible]}$
30	242409843.851202	$1.787810 \times 10^{-[illegible]}$
40	242409843.851202	$1.793488 \times 10^{-[illegible]}$
50	242409843.851202	$1.798276 \times 10^{-[illegible]}$

Based on table 2, in general FCM – PSO can achieve more minimum value of objective function than FCM in each iteration. more specifically, the minimum value of FCM objective function is in 30th iteration same with FCM – PSO in 30th iteration just achieve minimum value although in the next iteration until final iteration, the minimum value of FCM objective function still same with 30th, 40th, and 50th iteration. Thus, FCM has saturation point in 30th iteration different with FCM – PSO which have probabilities to increase or decrease in any iteration point.

Table 3 : Comparison between FCM and PSO - FCM for each iteration using Image Data (2c)

Iteration	Objective Function	
	FCM	FCM - PSO
10	247525172.936738	$1.918142 \times 10^{-[illegible]}$
20	246618054.261429	$1.931234 \times 10^{-[illegible]}$
30	246618047.515927	$1.894208 \times 10^{-[illegible]}$
40	246618047.445590	$1.911768 \times 10^{-[illegible]}$
50	246618047.445590	$1.968780 \times 10^{-[illegible]}$

Based on table 3, in general FCM – PSO can achieve more minimum value of objective function

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than FCM in each iteration. More specifically, the minimum value of FCM objective function is in 40th iteration but FCM – PSO in 30th iteration can achieve minimum value although in the next iteration until final iteration, the minimum value of FCM objective function still same with 50th iteration. Thus, FCM has saturation point in 40th iteration different with FCM – PSO which have probabilities to increase or decrease in any iteration point.

Table 4 : Comparison between FCM and PSO - FCM for each iteration using Image Data 2(d)

Iteration	Objective Function	
	FCM	FCM - PSO
10	235733509.449784	1.884801×10^{-7}
20	233692519.512613	1.881278×10^{-7}
30	233692517.538737	1.841460×10^{-7}
40	233692517.538737	1.867887×10^{-7}
50	233692517.538737	1.888008×10^{-7}

Based on table 4, in general FCM – PSO can achieve more minimum value of objective function than FCM in each iteration. More specifically, the minimum value of FCM objective function is in 30th iteration different with FCM - PSO in 50th iteration achieve minimum value although in the next iteration until final iteration, the minimum value of FCM objective function still same with 40th and 50th iteration. Thus, FCM has saturation point in 30th iteration different with FCM – PSO which have probabilities to increase or decrease in any iteration point.

Table 5 : Comparison between FCM and PSO - FCM for each iteration using Image Data 2(e)

Iteration	Objective Function	
	FCM	FCM - PSO
10	243368134.147873	2.134888×10^{-7}
20	240575970.214236	2.103890×10^{-7}
30	240575969.516353	2.101886×10^{-7}
40	240575969.516353	2.112810×10^{-7}
50	240575969.516353	2.184026×10^{-7}

Based on table 5, in general FCM - PSO can achieve more minimum value of objective function than FCM in each iteration. More specifically, the minimum value of FCM objective function is in 30th iteration same with FCM – PSO in 30th iteration achieve minimum value although in the next iteration until final iteration, the minimum value of FCM objective function still same with 40th and 50th iteration. Thus, FCM has saturation point in 30th iteration different with FCM – PSO which have probabilities to increase or decrease in any iteration point.

Table 6 : Comparison between FCM and PSO - FCM for each iteration using Image Data 2(f)

Iteration	Objective Function	
	FCM	FCM - PSO
10	239961053.673908	2.088818×10^{-7}
20	237102721.072324	2.108248×10^{-7}
30	237102661.076522	2.048872×10^{-7}
40	237102661.076522	2.088876×10^{-7}
50	237102661.076522	2.072888×10^{-7}

Based on table 6, in general FCM – PSO can achieve more minimum value of objective function than FCM in each iteration. More specifically, the minimum value of FCM objective function is in 30th iteration same with FCM – PSO in 30th iteration achieve minimum value although in the next iteration until final iteration, the minimum value of FCM objective function still same with 40th and 50th iteration. Thus, FCM has saturation point in 40th iteration different with FCM – PSO which have probabilities to increase or decrease in any iteration point.

In summary based on result from table 1-6 in section 5, in general, FCM – PSO can achieve more minimum objective function value for every iteration in all images data than original Fuzzy C-Means, due as stated Fuzzy C-Means objective function only achieve in local minimum [11]. More specifically, original FCM algorithm can achieve minimum objective function in 30th – 40th iteration and the value not changed for next iteration while FCM – PSO algorithm can achieve minimum value in 30th until 50th iteration. The difference is, in FCM – PSO after achieve minimum value between all iteration, there is possibility where objective function value is increase while in FCM, the objective function value is same with previous iteration if the value has been convergent or achieve minimum value.

6. CONCLUSION AND FUTURE WORK

Optimize objective function of Fuzzy C-Means Algorithm as segmentation algorithm using Particle Swarm Optimization algorithm is successfully developed. Based on comparison with original

Fuzzy C-Means without optimization stage, can be optimized with result objective function of original Fuzzy C-Means can be decreased after optimization stage. In detail, Based on section 5 which explains about the performance of proposed method using 6 images data, Fuzzy C-Means optimized by Particle Swarm Optimization and compared with original method, Fuzzy C-Means in brain tumor MRI image segmentation, proposed method perform better rather than original method. It is indicated with objective function of Fuzzy C-Means optimized by Particle Swarm Optimization can achieve more minimum that original Fuzzy C-Means for all experiments and proposed method can achieve more minimum value than original method in stable 30th iteration for each experiment, as described that Fuzzy C-Means only achieve local minimum [11]. This shows that Fuzzy C-Means optimized by Particle Swarm Optimization is an appropriate method for brain tumor MRI image segmentation.

This research only show and analysis of Fuzzy C-Means objective function which has been optimized using Particle Swarm Optimization, do not show the result in the form of brain tumor MRI images that have been segmented, so it is expected for further research to mapping objective function of Fuzzy C-Means that have been optimized using Particle Swarm Optimization become segmented image and compared the result with original Fuzzy C-Means.

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