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ENHANCED K-MEANS BY USING GREY WOLF OPTIMIZER FOR BRAIN MRI SEGMENTATION

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Abstract

Segmentation is an essential part of the detection and classification series. The best result of brain MRI detection was followed by the best segmentation process. Supporting brain MRI detection accurately, one of the ways could be used by increasing segmentation. This paper utilizes one of the segmentation methods which is called clustering. We propose a clustering approach using K-Means. K-Means has advantages easy to understand, fast process, and guarantees convergence. But it has drawbacks which are initialization cluster center randomly, sometimes it is given good results but sometimes it is not. Therefore, this research proposes to optimize the weak side of K-Means using a grey wolf optimizer. Initialization cluster center was chosen based on fitness value. The fitness value of this paper is Sum Square Error (SSE), we purpose to minimize the SSE of the population and searching new positions depend on Gray Wolf Optimization (GWO)'s rule. The final position of GWO would be initialized by K-Means. The series of our research steps are acquisition image, grayscaling, resizing, segmentation, and analysis performance based on MSE and PSNR. The best result of the purposed method is k=17 which PSNR (16.09) and MSE (15.99). GWO K-Means were given the best outcome segmentation brain MRI based on measuring error value and PSNR.

Keywords:

Gray Wolf Optimization, K-Means, MRI Segmentation, Sum Square Error

1. INTRODUCTION

Brain MRI is implemented for the recognition of such tumors [1]. Technology for increasing accuracy image segmentation MRI is the key part of a medical imaging application. The accuracy of the segmented image of the medical image such as the brain, prostate, etc. is the most important criterion to draw such an image processing and computer vision [2].

Image segmentation is a significant characteristic in field studies associated with the expanse of segmented brain MRI erase the astonishing structures from other brain problems [1]. Therefore, the outcome of a good segmented image will give greater accuracy for classifying several types of tumor and help on providing exposure about diagnosis properly. The problems about brain cells and tumors using the image segmentation approach have become a widely analyzed area [3] [4]. This thing is also supported [5] which segmentation is a serious problem in processing and evaluating MR images that impress the ultimate outcomes of the analysis. The good segmentation method will support better classifying MRI images.

There are many segmentation techniques is used by many scientists. Zaitoun and Aqel [6] presented segmentation techniques classified into two main categories segmentation using layer-based and block-based. Block-based segmentation is divided into region-based and edge-based. This research implements one technique at region-based, which is named clustering. Clustering is a common method used as an approach in pattern recognition and machine learning [7] [8]. Native clustering methods have bad performance in excessive dimensional data, therefore it leads to the ineffectively of similarity [8]. Clustering is the part of data mining called unsupervised learning, there is no training data set in the clustering approach.

K-Means is one of the clustering techniques, It has two advantages fast process, and easy to understand, behind the strength of K-Means, It has a drawback which is the best or the worst outcome of K-Means is influenced by determining cluster center at the beginning [9]. It is also strengthened by paper [9], [10] initialization centroid and local solution search can be affected in method and partition performance. There is a lot of research has been successful to finish the K-Means problem.

Dash [11] compared two methods to solve clustering problems using genetic algorithms and K-Means. The issue of the K-Means standard is quite sensitive to the initial positions of the centroid. Therefore the author [9] tried to handle the drawback of K-Means and changed the approach K-Means becomes GA. The result of this research is clustering based on genetic algorithms better than K-Means standard, but it has a long time complexity.

Raval and Jani [12] presented K-Means has two areas of concern for enhancing accuracy and efficiency that is the selection of initial centroid and assigning data nearest cluster center uses distance measure. This paper [10] used efficient methods for selecting the initial cluster value. The improved K-Means in this research emphasizes determining initialization centroid and grouping data into the closest centroid. The results of improved K-Means increase the speed and accuracy of the grouping process and reduce the computation complexity of K-Means standard.

Bonab and Hashim [7] explained the obstacle of K-Means such as the jeopardy of getting trapped into local optimality obstructs the clustering performance. This paper [7] implemented differential evolution and artificial bee colony to find the optimum centroid for the analysis data and compound algorithm to untangle the clustering issue. This research quiet success which is bee colony achieved optimum clusters to implement image segmentation in several light condition areas.

Rashid [13] presented the classification and prediction problems to solve academic performance research. This paper using classification methods such as RNN, MLP, CMLP, BPNN, Naïve Bayes, and Random Forest. But the satisfaction of the level of existing systems is not promising. Therefore the author [13] proposed a hybrid system to solve this problem used an altered RNN with an adapted GWO. This paper is implemented to enhance the instruction of the faculty and increase the scholars studying experiences. Their hybrid method is utilized to forecast students' results.

Mirjalili et al. [14] implemented a new metaheuristic approach is called grey wolf optimizer. The trigger of this research is there is no swarm intelligence technique in the literature imitating the leadership hierarchy of grey wolves. This reason motivated the author [14] to make a mathematical model based on the social behavior of grey wolves. Grey wolf optimizer (GWO) was examined by using other methods: PSO, GSA, DE, and ES. The result has obtained GWO is better than PSO, GSA, DE, and ES.

Rayarooth and Sivaradje [15] have researched about water distribution system (WDS). This research focused on water leakage detection approaches. The issue of their research is some existing methods like Convolutional Neural Network-Support Vector Machine (CNN-SVM) and Particle Filter (PF) failed to improve the performance of accuracy and timely processing. Therefore, the paper [13] implemented another method used bivariate correlation and sensitivity analysis based on grey wolf optimization. This paper had succeeded to improve the accuracy of water leakage detection compared with CNN-SVM and PF.

Based on papers [13]–[15] have explained that it could be the top priority for choosing grey wolf optimizer which is the combination RNN-GWO could be more stable of encountering the overfitting problem and solving the local minimum problem [13]. GWO also showed superior exploitation in the case of the unimodal functions and given highly competitive results compared to GSA, PSO, DE, ES, and EP [14]. Therefore this research implements segmentation brain MRI utilizing the increasing K-Means performance using grey wolf optimizer. Our contribution in this research is enhancement K-Means using one of swarm intelligence approaches to reduce error segmentation brain MRI compared K-means conventional. Our paper is arranged as follows: section II-IV describes theories. Section V draws the used research method, section VI shows results, and the rest of this paper is the conclusion and references.

2. K-MEANS

K-Means is one of the clustering approaches which is it divides images into k clusters. Grouping into k-cluster depends on the high similarity between data and cluster center [12], [16]. The fundamental of K-Means is a determination of initializing cluster center at the beginning.

Step 1: Determining the number *k* cluster.

Step 2: Initializing cluster center randomly.

Step 3: Counting the measure between cluster center and data using Euclidean distance is shown Eq.(1). For example, If data $x=(x_1, x_2, x_3,...,x_n)$ and cluster $c = (c_1,c_2,c_3,\ldots,c_n)$

$$d(x,c)=\sqrt{(x_1-c_1)^2+(x_2-c_2)^2+...+(x_n-c_n)^2} \quad (1)$$

Step 4: Grouping data based on cluster.

Step 5: Specifying recent cluster centers based on the Eq.(2).

$$C_j=\frac{1}{n_j}\sum_{x_i\in c_i} x_i \quad (2)$$

Step 6: Doing iteration until convergence achieved.

3. SWARM INTELLIGENCE

Some scientists emphasize in specific animal behavior which is becoming their inspiration, cuckoo search, ant colony optimization was inspired by searching food behavior of ants [17], bee colony was analogized as the behavior of bees on consisting of food sources, and each food source is represented as a solution of the problem. Particle swarm optimization is determined by personal best and global best position [18]. This research would be focused on one of the parts of swarm intelligence methods is called the grey wolf optimizer. The optimization methods can be used in several cases, classification, clustering, pattern recognition, and so on. A lot of researches and review articles have been announced that authenticate the qualification of artificial swarm intelligence to strengthen the intelligence of person categories [19].

4. GREY WOLF OPTIMIZER

In Ali Mirjalili's research, grey wolf optimizer is inspired by the behavior of the wolves hunt with their group [14]. Grey wolves include apex predator species, and mostly they live in a pack. The leader of the grey wolf is alpha which it has culpable for decision making, below the alpha called beta are subordinate wolves to support alpha making decision and activities in the pack, and the third named omega, they have a duty as messengers of the pack, the rest of these three that called delta [14]. The social hierarchy of grey wolves optimizer analogized to first solution namely α (alpha), the second solution is β (Beta), and the last is δ (Omega). There are many phases in group hunting of grey wolves.

- Tracing, chasing the target, and moving closer to the prey.
- Pursuing, encircling, forcing, and disrupting until the prey cannot move.

$$Dist(t+1) = |C*X_p(t) - A*X_{gw}(t))| \quad (3)$$

$$X_{gw}(t+1) = X_p(t)\text{-}A*\mathrm{Dist}_{(t+1)} \quad (4)$$

where,

t is the current iteration,

A and C specifies coefficient value,

X_p is the vector position of prey, and

X_{gw} shows the position of a grey wolf.

The calculation coefficient vector is formulated with Eq.(5) and Eq.(6).

$$A= 2a*r_1*a \quad (5)$$

$$C=2*r_2 \quad (6)$$

where,

a describes linear value which is counted down from 2 until 0 following iteration,

r_1 and r_2 are random vectors [0,1].

5. PROPOSED METHOD

We implement our proposed algorithm in five images. Based on proceeding [20] we use the same cluster to compare the algorithm between K-Means and K-Means GWO. Our research steps are covering acquisition image, resizing, segmentation using K-Means conventional and GWO K-Means, and finally doing analysis performance.

The acquisition uses the format jpeg/jpg. The output of the segmentation process is the intensity pixel value based on the number *k* cluster. If k=5, then output intensity pixel between 1 and 5. Image region has small pixel intensity would be closed to black and big pixel intensity would be changed to white. The Block diagram research method is shown in Fig.1.

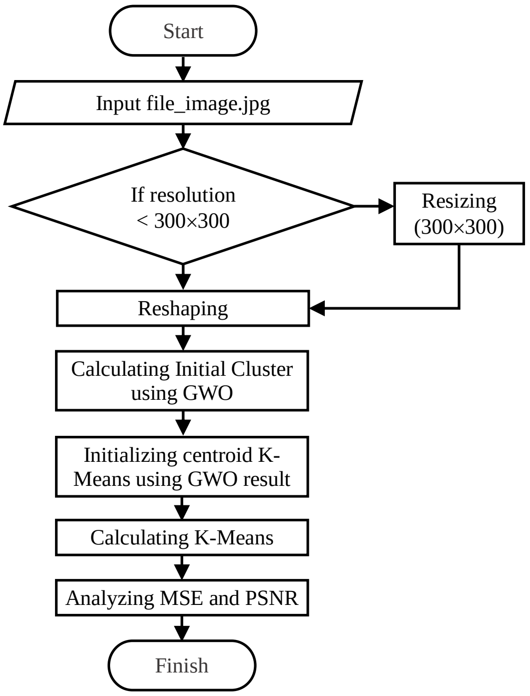


Fig.1. Flowchart of Proposed Method

- To perform image segmentation, firstly we have to convert image RGB into grayscale, calculating mean value of Red, Green and Blue (RGB). Multiplying R, G and B with some certain value.
- There are several resolutions on five images, big resolution could be slowing down the computation process. Therefore, this paper implements resizing images. We assign a maximum resolution of 300×300.
- Reshaping image change size height *x* width pixel into multiply height and width as total rows and one column

$$B=reshape(Grayscale,sz) \tag{7}$$

- Assigning the reshaped image to be the dataset

5.1 GREY WOLF OPTIMIZER

Step 1: Initializing population of wolves, number k cluster, alpha, beta, omega, and maximum iteration.

Step 2: Determining centroid randomly according to number k cluster and then entry into the population. One individual is n set centroid and the population is n number wolf.

$$\text{Population} = \underbrace{[C_1,C_2,C_3]}_{\text{Individu 1}},\ \underbrace{[C_4,C_5,C_6]}_{\text{individu 2}},\ldots,[C_n]$$

Step 3: Doing iteration 1 until defined maximum iteration has been achieved.

a. Calculating $\vec{a}$ using formula Eq.(8)

$$\vec{a} = 2-2\left(\frac{iteration}{\max\_iteration}\right) \tag{8}$$

b. Calculating First SSE as a Fitness value using Eq.(9) for the first iteration. Assigning alpha, beta, and omega based on fitness value.

$$SSE = \sum_{j=1}^{k}\sum_{x\in c_i} d^2\left(m_j, x\right) \tag{9}$$

c. Calculating distance alpha, beta, and omega following Eq.(3)

d. Calculating position vector alpha, beta and omega is defined by Eq.(4)

e. Assigning new position is formulated by Eq.(10)

$$X_{(t+1)}=(X_{gw}1+X_{gw}2+X_{gw}3)/3 \tag{10}$$

where, $X_{gw}1$ shown position vector alpha, $X_{gw}2$ shown position vector beta, $X_{gw}3$ is position vector omega.

5.2 K-MEANS

Step 1: Using final position is shown in Eq.(10) as an initial cluster center on K-Means.

Step 2: To calculate distance measure between data and the obtained cluster center, we use Euclidean distance as in Eq.(1), assign all the points to the closest cluster center.

Step 3: Updating cluster center uses the calculated average value of all data points inside cluster according to Eq.(2).

Step 4: Terminating condition, if there is no change in its values (centroids have stabilized) or the defined maximum iteration has been achieved.

Step 5: Returning reshaped image into image binarization.

6. RESULTS

Brain MRI has an almost similar grayscale intensity, thus these things often are found in different analyses visually. Material this research has been taken from kaggle.com. Each pixel has a different resolution. To find out the performance of the segmentation image, a total of five sample images have been implemented and started from the gray scaling process, resizing image has resolution bigger than 300×300, and reshaping image (Table.1).

Table.1. Sample Brain MRI

Name	Resolution	Resized
no 1.jpg	630×630	300×300
no 2.jpg	630×630	300×300
no 22.jpeg	207×243	-
no 24.jpeg	235×214	-
Y11.jpeg	400×369	300×300

After finishing the resizing image, we convert resized image into grayscale.

$$Greyscale(i,j):0.299(i,j,R)+0.587(i,j,G)+0.114(i,j,B)$$

After the grayscaling process, we convert the grayscale image using reshape array becomes a new size.

[rows,cols] = size(image_double);

Image_reshape = reshape(image_double, rows*cols,1);

$$
\begin{array}{ccc}
104 & 248 & 62 \\
187 & 30 & 149 \\
95 & 89 & 232
\end{array}
\qquad
\begin{array}{c}
104 \\ 248 \\ 62 \\ 187 \\ 30 \\ 149 \\ 95 \\ 89 \\ 232
\end{array}
$$

Reshaped images would become datasets. Joining all clusters into one individual wolf and determining total individual wolves would be processed. We give an example of five clusters on 2 individual wolves.

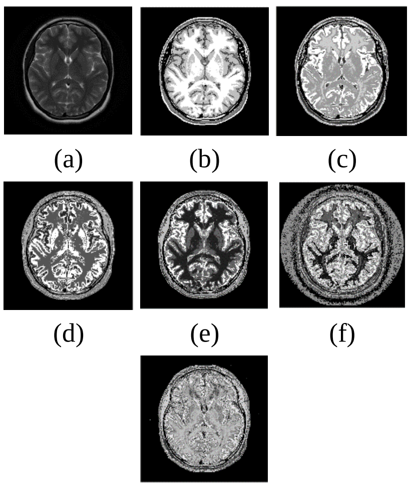
$$ind_1=(104,248,62,187,149)$$

$$ind_2=(62,30,95,89,232)$$

Calculating distance measure by using Euclidean and getting SSE value Eq.(8). Selecting the three best wolves to depend on minimum value SSE as alpha, beta, and omega. The next process calculates the distance (D) and position (X) from alpha, beta, and omega using Eq.(3) and Eq.(4).

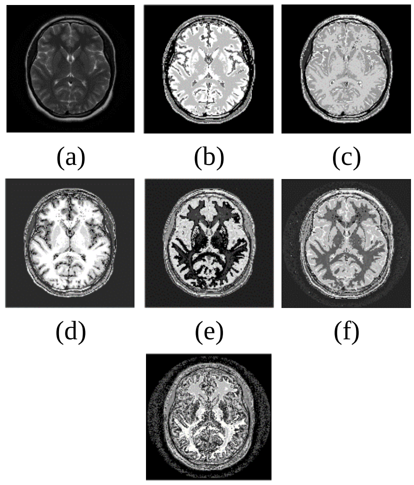
The outcomes of image segmentation based on K-Means native and K-Means Grey Wolf Optimizer. In this research, each image is researched by using 6 clusters, and each cluster would be implemented five times experiment and calculating average MSE and PSNR. Overall we implemented 30 tests for K-Means and 30 tests for GWO K-Means for one sample image. This research implemented a total of 6 clusters based on research [20].

The Fig.2 and Fig.3 are one of the five samples of segmentation images. Sample original image examined sequentially following 5, 6, 7, 9, 15, and 17 total clusters. GWO and K-Means clustering approach contributed to get suitable result, region with the segmented brain MRI was entirely detected. Although K-Means algorithm is high speed but it does not guarantee to get a well-segmented image.



(a) (b) (c) (d) (e) (f) (g)

Fig.2. Segmentation GWO K-Means: (a), (b) k=5, (c) k=6, (d) k=7, (e) k=9, (f) k=15, (g) k=17



(a) (b) (c) (d) (e) (f) (g)

Fig.3. Segmentation K-Means: (a) Original image, (b) k=5, (c) k=6, (d) k=7, (e) k=9, (f) k=15, (g) k=17

Furthermore, this paper utilizes MSE and PSNR as an evaluation measure based on paper [21]. According to research [21] said the measurement good clustering method is the enhancement image quality will be accompanied by big PSNR value, but it seems in contrast when MSE value will be small.

For obtaining PSNR, firstly we have to calculate MSE using Eq.(11).

$$MSE=\frac{1}{a\times b}\sum_{i=0}^{b-1}\sum_{j=0}^{a-1}\left(X_{a,b}-Z_{a,b}\right)^2 \tag{11}$$

When MSE was found then PSNR could be calculated using Eq.(12). PSNR is the collation between the maximum measured signal and noise value influences on its signal, in this research, PSNR is utilized to find out the quality of segmented image and original image grayscale.

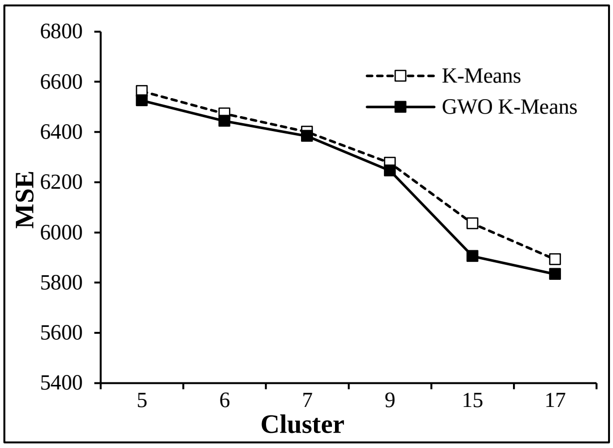
$$PSNR=10\log_{10}\left(255^2/MSE\right) \tag{12}$$

The Eq.(10) and Eq.(11) are shown analysis of five images using different five clusters. We do the comparison between GWO K-Means and K-Means native approach based on PSNR and MSE. Surprisingly k total cluster 6 and 7 does not get good value in fifth (5th) image, total individual wolves in population was obtained which have a big MSE value for 5 times test. The first reason is determining the centroid of each wolf implemented randomly. Therefore, fitness value (SSE) would be random too. The second is total individual on population and the number iteration of GWO could be added but this paper was determined by the same total wolves on population.

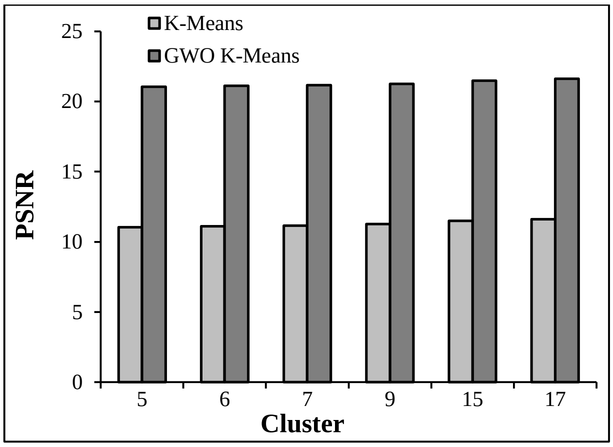
Based on Fig.4, the result shows when the number k cluster is increased from 5, 6, 7 until 17, the error value has decreased and the accuracy has enhanced. GWO K-Means reduced the error value of K-Means almost for all images. The results of the comparison between K-Means and GWO K-Means using MSE and PSNR are based on [21] which means our research method has a bigger PSNR than K-Means native and less MSE than K-Means standard, on the other word our research have good clustering approach.

Table.2. Comparison Results of K-Means and Proposed method

File	Comparison Method	MSE/PSNR					
		Cluster size 5	Cluster size 6	Cluster size 7	Cluster size 9	Cluster size 15	Cluster size 17
no 1.jpg	K-Means	1998 /15,12	1971/15,18	1940/15,25	1.890/15,37	1765/15,66	1683/15,87
	GWO K-Means	1988,6/15,15	1956,4/15,22	1926/15,28	1.868/15,42	1699/15,83	1669/15,91
no 2.jpg	K-Means	1956,4/15,22	1908/15,33	1898/15,35	1.840/15,48	1695/15,84	1645/15,97
	GWO K-Means	1932,2/15,27	1890,4/15,37	1881/15,39	1.817/15,54	1671/15,90	1599/16,09
no 22.jpeg	K-Means	9795,6/8,22	9711/8,26	9608/8,30	9435 / 8,38	9105/8,54	8926/8,62
	GWO K-Means	9774,2/8,23	9657/8,28	9573/8,32	9396 / 8,40	9045/8,57	8826/8,67
no 24.jpeg	K-Means	8810,4/8,68	8704/8,73	8607/8,78	8456 / 8,85	8183/9,00	7976/9,11
	GWO K-Means	8772,8/8,70	8636/8,77	8587/8,79	8425 / 8,87	7849/9,18	7887/9,16
Y11.jpeg	K-Means	10251/8,02	10071/8,10	9945/8,15	9760 / 8,23	9429/8,39	9229/8,48
	GWO K-Means	10157,4/8,06	10081/8,10	9949/8,15	9722 / 8,25	9262/8,46	9183/8,50



(a) MSE



(b) PSNR

Fig.4. Average performance MSE and PSNR of all images

7. CONCLUSIONS

Brain MRI Segmentation using GWO K-Means shown the best outcome for k=17 which MSE value shown the most minimum value and PSNR shown most maximum value from other existing number clusters. Overall measuring of error value and PSNR has been proven GWO supported best initialization centroid K-Means to segment brain MRI. For each cluster was started from k=5 until k=17. Our research has been successfully reduced MSE value and followed the increase of PSNR in the case of Brain MRI Segmentation.

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