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A novel modified particle swarm optimization algorithm with mutation for data clustering problem

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***Abstract*— Particle Swarm Optimization (PSO) and K-Means (KM) are widely used for solving data clustering. KM encounters the problem of initializing the cluster centers and the problem of trapping in local optimum. When PSO is applied with KM, it can decrease two problems from KM. Hence, the hybrid clustering technique based on PSO and KM that can enhance performance of clustering is more than using KM alone. However, the hybrid clustering technique encounters the trapping in local optimum problem. To solve this problem, this paper proposed improving hybrid technique by the mutation operation is applied with particles of PSO when swarm traps in local optimum. The proposed technique is tested on eight datasets from the UCI Machine Learning Repository and gives more satisfied search results in comparison with PSOs for the data clustering problems.**

Keywords- Data Clustering; Particle Swarm Optimization; Optimization; Mutation Operation; K-Means

I. INTRODUCTION

Particle Swarm Optimization (PSO) is inspired from the behavior of flying bird and their communication mechanism [1], [2]. PSO is a stochastic global optimization technique. PSO is used for solving optimization problems. The goal of PSO is finding the global optimum of a fitness function. PSO has many pros such as rapid convergence, simplicity, and little parameters to be adjusted. However, the con of PSO is high chances of trapping in the local optimum [3].

The data clustering [4], [5] is optimization problem and an unsupervised learning technique. The unsupervised learning technique is not any training data with class labels. The object comprises many attributes. The attribute can be used to identify group of object or class of object. The goal of data clustering is dividing to groups of objects. The objects have similarity attributes are in same group. On the other hand, the objects have differential attributes are in other groups.

The Data clustering is applied with many application areas, such as bioinformatics, machine learning, information retrieval, data analysis, pattern recognition and image processing [6], [7]. The well-known technique for applying to clustering is the K-Means clustering (KM). The output clusters of KM are called "hard" or "crisp" [8]. The cons of KM are the problem of initializing the cluster centers and the problem of trapping in local optimum [6]. To overcome this cons, many papers used PSO apply with KM (hybrid clustering technique) [9-12]. The effect of applying PSO with KM can increase distribution of population. Hence, it can decrease the problem of initializing the cluster centers and the problem of trapping in local optimum. The experiment results of these papers showed that these techniques can get better solutions than KM alone.

E. Hojjat and D. Farnaz [10] proposed Fuzzy K-Means (FKM) replaces KM or PSO apply with FKM (PSOFKM). FKM can decrease problem of initializing the cluster centers better than KM. [13], [14]. So, the solution of PSOFKM is better than that of compared algorithms.

R. Jensi [11] proposed the hybrid clustering algorithm based on PSO with Levy Flight and KHM algorithms (PSOLF-KHM). The K-Harmonic Means (KHM) suffers the problem of trapping in local optimum [15]. So, the Levy flight (LF) applies with KHM and PSO. The Levy flight can increase high exploration. It can enhance clustering performance. The experimental results show that the solution of the PSOLF-KHM algorithm is better than that of compared algorithms.

However, PSOLF-KHM and PSOFKM cannot improve solutions when the problem of trapping in local optimum occurs. Hence, these techniques may have rarely the clustering performance in long running.

The mutation operator is technique comes from genetic algorithm (GA) [16]. The main concept of mutation operator is random to change a little position of chromosomes or particles (for particle swarm algorithm). Many researchers proposal many mutation techniques such as: the mutation operator is considered from particle diversity [17], the mutation operator is considered from the best particle that is stagnant [18].

To overcome this weakness, many researchers [19-21] increased diversity into the population of PSO. They add the mutation technique or the particle re-initialization technique or the particles reposition technique into the process of PSO. The experiment results of these papers showed that these techniques can decrease and solve the problem of trapping in local optimum. Moreover, these techniques get better solutions than the standard PSO for solving the benchmark functions problem.

To handle the problem of trapping in the local optimum, this paper proposed a novel mutation technique applies with PSO for solving data clustering problem when PSO happens to trap in local optimum. The proposed technique is called

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that modified particles swarm optimization with mutation or PSOM. A set of dataset in the UCI Machine Learning Repository is used to compare the standard PSO [9] by source code from [12], PSOFKM [10], PSOLF-KHM [11], and the proposed technique. The results show that the solutions quality and the algorithm reliability of the proposed technique are better than other compared algorithms in all tested datasets.

II. Background

A. Particle Swarm Optimization

In standard PSO, each member of the population is called a "particle". Each particle contains its position and its velocity. Each individual particle executes searching in the search space according to its velocity, the best position found in the whole swarm (GBEST) and the individual's best position (PBEST). PSO starts with randomizing particle positions and their velocities, and the evaluation of the position of each particle is calculated from the objective function of the optimization problem. In each generation, each individual particle updates its position and velocity according to the expression below:

$$V_{id}' = \varpi V_{id} + \eta_1 rand()(P_{id} - X_{id}) + \eta_2 rand()(P_{gd} - X_{id}) \quad (1)$$

$$X_{id}' = X_{id} + V_{id}' \quad (2)$$

Where X_{id} is the previous positions of i particle and d dimension, X'_{id} is the current positions of i particle and d dimension, V_{id} is the previous velocity of i particle and d dimension, V'_{id} is the current velocity of i particle and d dimension, P_{id} is PBEST of i particle and d dimension, and G_{id} is GBEST of d dimension. ϖ is an inertia weight, η_1 and η_2 are acceleration constants, and rand() is the random number generated uniformly in the range [0, 1]. A limit velocity calls V_{max}. If calculate velocity of a particle exceeds V_{max}, it is replaced value of V_{max}.

B. K-Means Clustering

In standard KM, each data is called "object". The group of object is called "class" or "centroid vector". Both class and object contain attributes. The attributes of object and the attributes of classes are used to classify by Euclidean distance technique [9]. The main concept of KM is can be summarized as follows: the smallest Euclidean distances from the attributes of object to the attributes of one class, this object is assigned into this class. The standard KM starts with randomizing attributes of classes and the evaluation of each class is calculated from the expression below:

$$d(z_p, m_j) = \sqrt{\sum_{k=1}^{N_d} (z_{pk} - m_{jk})^2} \quad (3)$$

$$Fitness = \frac{\sum_{j=1}^{N_c} [\frac{\sum_{\forall z \in C_{ij}} d(z_p, m_j)}{|C_{i,j}|}]}{N_c} \quad (4)$$

Where N_d is the number of attributes, N_c is the number of classes, Z_p is the object p, Z_{pk} is the attribute k in the object p, m_j is the class j, m_{jk} is the attribute k in the class j, $|C_{i,j}|$ is the number of object belonging to class j, and $d(z_p, m_j)$ is the distance between the object p and the class j. This algorithm can be stopped when the maximum number of iterations has been exceeded.

C. PSO with Data Clustering

The standard PSO was proposed to solve the benchmark function problem. To PSO can apply with the data clustering problem, the objective function and particle position are modified. A single particle represents the class [9]. The fitness of panicle is measured as (3) and (4). In addition to previous mention, process of PSO with data clustering is similar to process of the standard PSO.

III. Related Works

A. Particle Swarm Optimization with Fuzzy K-Means

Particle Swarm Optimization with Fuzzy K-Means (PSOFKM) improves clustering performance of PSO by using the Fuzzy K-Means technique. The main concept of PSOFKM is can be summarized as follows: each generation, FKM process is applied. After process of FKM finished, PSO process is applied. This process continues until a stopping criterion is met.

B. Particle Swarm Optimization with Levy Flight and The K-Harmonic Means

The hybrid clustering algorithm based on PSO with Levy Flight algorithms and KHM algorithms (PSOLF-KHM) improve clustering performance of PSO by using KHM technique and The Levy flight (LF). The main concept of PSOLF-KHM is can be summarized as follows: Each generation, PSO process is applied. For updating position and velocity step, the Levy Flight algorithm is applied instead of updating position and velocity of the standard PSO. After process of PSO finished, KHM process is applied. This process continues until a stopping criterion is met.

IV. Modified Particles Swarm Optimization with Mutation

However, the cons of PSOFKM and PSOLF-KHM have many points. The first is the complication from adjusting parameters. PSOLF-KHM has parameters of KHM, LF that is added from the standard PSO. PSOFKM has parameters of FKM that is added from the standard PSO. These parameters are floating point values and are not concept for adjusting them. To solve problem effectively, these parameters must be adjusted appropriately. The second is the increased runtime. For PSOLF-KHM, process of KHM in running is added. For PSOFKM, process of FKM in running is added. Hence, runtime of these techniques are slower than runtime of the standard PSO. Finally, PSOFKM and PSOLF-KHM encounter the problem of trapping in local optimum. These

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techniques have not process for solving when the problem of trapping in local optimum occurs. When trapping in local optimum occurs, the solution is constant until searching finishes. Hence, PSOFKM and PSOLF-KHM may have rarely the clustering performance in long running.

The mutation technique should be used when swarm trap or trend to trap in local optimum in order to distribute particles to search in other area. The easy indicator of the trapping in local optimum state is the unchanged number of consecutive GBEST. Thereby, this paper proposed the mutation period (MP) is considered from the unchanged number of consecutive GBEST. If the mutation period is set too small, particles will be reset before convergence. On the other hand, if the mutation period is set too large, particles remain trapping in local optimum instead of search in other areas. Hence, the mutation period should be adjusted too large because it is not distribute searching of PSO. Moreover, the number of mutated particles are the mutation rate (MR) or the mutation percent. The mutation rate should be adjusted too large because it can jump out local optimum. So, the both MP and MR can adjust easily and have easy concept for adjusting them. Hence, this paper proposes the mutation technique apply with particle swarm optimization to solve data clustering problem or modified particles swarm optimization with mutation (PSOM). The concept of proposed technique is explained as follows: Each generation, PSO process is applied. Then, if unchanged number of consecutive GBEST is more than MP, the mutation technique is applied to jump out local optimum. Pseudo code of PSOM is shown below:

```
Initial position and velocity of each particle
Initial PBEST, GBEST, RBEST
For gen = 0 to MAXGEN
  For i = 0 to N
    Evaluate particle fitness according to formula (4)
    If F(Xi) < F(PBESTi)
      PBEST = Xi
    End If
    If F(Xi) < F(GBEST)
      GBEST = Xi
    End If
    If F(Xi) < F(RBEST)
      RBEST = Xi
    End If
    Update particle position according to formula (1) and (2)
  End For
  If F(GBEST) = TGEBST
    CGBEST++
  Else
    CGBEST = 0
    TGEBST = F(GBEST)
  End If
  If CGBEST ≥ MP
      CGBEST = 0
      Reset GBEST, PBEST
      For p = 1 to N
        For j =1 to Nc
          For k =1 to Nd
            If MR > rand() then
              Initial velocity of p particle according to formula (5)
              Initial position of p particle according to formula (6)
            End If
          Next k
        Next j
      Next i
  End If
Next gen
```

Where N_d is the number of attributes, N_c is the number of classes, N is the number of particles, RBEST is the best answer which is not reset. $F(X_i)$ is fitness of i particle, $F(PBEST_i)$ is fitness from PBEST of i particle, $PBEST_i$ is PBEST of i particle, F(GBEST) is fitness of GBEST, CGBEST is the unchanged number of consecutive GBEST. TGEBST is temporary fitness for checking changing of GBEST. MAXGEN is the maximum generation.

$$x_{id} = LL_d + rand()(UL_d - LL_d) \quad (5)$$

$$V_{id} = -V_{\max,d} + 2rand()(V_{\max,d}) \quad (6)$$

$$V_{\max,d} = 0.1(UL_d - LL_d) \quad (7)$$

Equation (5) and (6) is mutation equations used in PSOM. Equation (7) is calculation V_{max} of d attribute, UL_d is the maximum value of d attribute, LL_d is the minimum value of d attribute, $V_{max,d}$ is the maximum velocity of d attribute.

The main concept of applying the mutation technique with PSO of PSOM is similar to that of the mutation and reposition techniques apply with PSO (MRPSO) from reference [20]. It is increasing distribution of particles. PSOM is used to solve data clustering problem, while MRPSO is used to solve benchmark functions. The solving data clustering problem is different from the solving benchmark functions. PSO encounter premature convergence problem and trapping in the local optimum problem for solving data clustering problem is much more than that for solving benchmark functions. Hence, PSOM is added the new techniques from applying mutation techniques, such as reset GBEST, reset PBEST, and Initial velocity and position of particles. Moreover, MR defined to small value to reset frequently and MP defined to large value to wide distribution. The goal of these techniques is increasing distribution of particles to enough for escape local optima.

V. EXPERIMENTS AND RESULTS

A. Datasets

The proposed algorithm is tested on eight datasets, listed in Table 1. The results of PSOM on the datasets are compared with PSO, PSOLF-KHM, and PSOFKM.

TABLE I. DETAILS OF DATASETS.

Order	Name	Datasets	Attributes	Classes
1	IRIS	150	4	3
2	WINE	178	13	3
3	GLASS	214	9	6
4	HEART	270	12	2

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Order	Name	Datasets	Attributes	Classes
5	CANCER	286	8	2
6	ECOLI	336	7	8
7	CREDIT	1000	24	2
8	YEAST	1484	8	10

B. The measures of algorithm performance

The measures of algorithm performance in the experiments are as follows: F-Measure (FM) is a famous evaluation measure. FM uses the ideas of precision and recall from information retrieval [6]. The precision P(i,j) and recall R(i,j) for each class i of each cluster j are calculated as:

$$P(i,j) = \frac{T_p}{T_p + F_p} \quad (8)$$

$$R(i,j) = \frac{Tp}{T_p + F_n} \quad (9)$$

$$F(i,j) = \frac{2 \times P(i,j) \times R(i,j)}{P(i,j) + R(i,j)} \quad (10)$$

Where T_p is true positive, F_p is false positive, F_n is false negative, F(i,j) is F-Measure. The average correct number (ACN) is the average of the correct number from predict of algorithm in the final generation from all running. FM and ACN indicate the clustering efficiency of an algorithm. The bigger FM and ACN are, the higher the quality of clustering is. SD is the standard deviation of FM. SD indicates the clustering reliability of an algorithm. The bigger SD is, the higher the reliability of clustering is.

C. Parameters Setting

Parameters for all experiments are as follows: acceleration constants of η_1 and η_2 are both set to be 1.45, ω = 0.75, the number of population is 100. The number of experiments of each function is 10 runs. The maximum iteration is 5000.

The non-PSO parameters for the compared algorithm parameters (PSOFKM, PSOLF-KHM) are set according to suggested by the original papers. Except parameters as follows: For PSOFKM, m = 1.5, ε = 0.001, p = 4 and η = 0.000001. For KHM, P = 2.5.

For proposal algorithm, MP is set as 5 and MR is set as 0.3. This research is conducted by a personal computer of AMD FX-8320 with 3.5 GHz CPU, 8 GB RAM and Visual C++ 2010 as the programming language. All datasets are used in experiment are from datasets.

To prove the diversity of PSO and the diversity of PSOM, this paper uses the population average distance amongst points (D(t)) [17] is described as following:

$$d(t) = \frac{1}{M \times L} \sum_{i=1}^{M} \sqrt{\sum_{d=1}^{D} (x_{id} - \bar{p}_{id})} \quad (11)$$

Where L represents the diagonal length of search space, M represents the size of the population, D represents the dimension of the solution space, x_{id} represents the d dimension coordinate values of the i particle, and $\bar{p}_{id}$ represents the average value of the d dimension coordinate values of all particles. If the diversity has much value, population are much distributed.

D. Experiment of the proposed algorithm

From the experimental results of Table 2 and Table 3 show that the quality solution of PSOM is better than that of PSO, PSOFKM, and PSOLF-KHM because of its highest FM and ACN all datasets. From the experimental results of Table 4 show that the reliability of PSOM is better than that of PSO, PSOFKM, and PSOLF-KHM because of its lowest SD all datasets. Hence, PSOM outperforms PSO, PSOFKM, and PSOLF-KHM in case of reliability and quality solution. The experiments can prove that the mutation technique can increase the clustering performance of PSO for data clustering. PSO, PSOFKM, and PSOLF-KHM encounter the problem of trapping in local optimum. Hence, these techniques may have rarely the clustering performance in long running while PSOM have process for handling the problem of trapping in local optimum. Hence, the mutation technique can enhance clustering performance in long running. In case of IRIS, the clustering results of PSOM yields the optimum point in all running rounds because a number of evaluations are enough for solving this problem. For other datasets, the clustering results of PSOM cannot yields the optimum point because a number of evaluations are not enough for solving these problems.

TABLE II. COMPARATIVE F-MEASURE (FM) OF PSO, PSOFKM, PSOLF-KHM AND PSOM ON DATASETS.

Datasets	Algorithms			
	PSO	***PSOFKM***	***PSOLF-KHM***	***PSOM***
IRIS	0.654	0.775	0.81	1
WINE	0.56	0.624	0.65	0.794
GLASS	0.319	0.332	0.376	0.622
HEART	0.471	0.542	0.533	0.734
CANCER	0.492	0.508	0.51	0.723
ECOLI	0.26	0.304	0.268	0.592
CREDIT	0.486	0.528	0.522	0.554
YEAST	0.183	0.213	0.21	0.261

TABLE III. COMPARATIVE THE AVERAGE CORRECT NUMBER (ACN) OF PSO, PSOFKM, PSOLF-KHM AND PSOM ON DATASETS.

Datasets	Algorithms			
	PSO	***PSOFKM***	***PSOLF-KHM***	***PSOM***
IRIS	107.6	120.3	125.1	150
WINE	116	121.1	124.6	142.9
GLASS	112.4	115.1	116.9	154
HEART	157.3	163.8	165.7	202.7
CANCER	189.2	194.3	198.3	224
ECOLI	171.6	197.2	192.4	246.5
CREDIT	693.9	707.7	709.9	720.7
YEAST	568.4	606.1	616.2	718

TABLE IV. COMPARATIVE THE STANDARD DEVIATION (SD) OF PSO, PSOFKM, PSOLF-KHM AND PSOM ON DATASETS.

Datasets	Algorithms

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	PSO	*PSOFKM*	*PSOLF-KHM*	*PSOM*
IRIS	0.115	0.092	0.093	0
WINE	0.102	0.102	0.068	0.021
GLASS	0.056	0.034	0.035	0.023
HEART	0.097	0.098	0.095	0.001
CANCER	0.067	0.056	0.072	0.003
ECOLI	0.108	0.066	0.099	0.013
CREDIT	0.033	0.028	0.039	0.025
YEAST	0.034	0.036	0.03	0.026

E. Experiment of the diversity of the proposed algorithm

From Fig. 1, the red line or the solid line is the logarithm of the diversity of PSO for iris data. The blue line or the dot line is the logarithm of the diversity of PSOM for iris data. Two lines are calculated from (11) and run 1000 generation. This graph shows that the diversity of PSOM is more than that of PSO. Line of PSO decrease then it is stable while line of PSOM decrease then the mutation is executed. It affects particles that are distributed and the line graph is much increased instantly. So, PSOM try to maintain the population diversity.

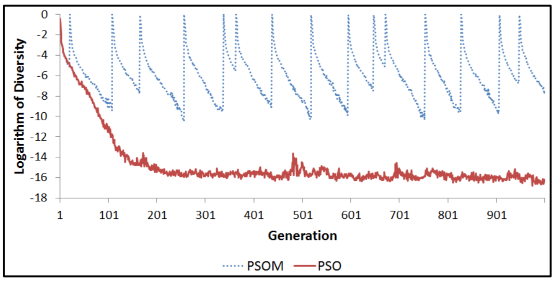

Figure 1. The diversity curves of PSO and PSOM for iris data.

VI. CONCLUSION

The main weakness of PSO and KM for solving data clustering problem is the problem of trapping in local optimum. To solve this problem and enhance population distribution, Fuzzy K-Means technique, K-Harmonic Means technique and Levy Flight technique are applied with PSO. These techniques cause the complication of adjusting parameter and increasing search time. Moreover, these techniques have not process for handling the problem of trapping in local optimum. So, these techniques can not improve solution in long running. To handle the problem of trapping in local optimum, the mutation technique is applied with PSO when population occur the trapping in local optimum. The proposed technique is called that PSOM. PSOM can deal with the problem of trapping in local optimum and improve clustering performance of PSO in long running. From the experimental results show that the proposed PSOM outperforms PSO, PSOFKM and PSOLF-KHM with regard to the reliability and quality of solutions in all datasets.

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