PATTERN REDUCTION ENHANCED ANT COLONY OPTIMIZATION CLUSTERING ALGORITHM

by Dwi Taufik Hidayat

Pattern Reduction Enhanced Ant Colony Optimization Clustering Algorithm

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***Abstract*—Ant Colony Optimization is the optimization method used for the analysis of the cluster. This method performs clustering data well. This method has limitations on computation time.This paper proposed a method of pattern reduction enhanced ant colony optimization to resolve the problem. Functions reduction pattern used to bypass loop system. This function ensures pheromone value if it meets certain iteration, so the next ant agent definitely choose the path that has been determined. The test is done through testing parameters and test accuracy. accuracy test compared with ant colony optimization method(ACO) with the results of the proposed method has the advantage of computing time. The test results show that the proposed method has 46 second faster than ACO method (73 second) for iris dataset, 141 second faster than ACO method (272 second) for wine dataset, and 150 second faster than ACO method (204 second) for synthetic dataset.**

Keywords*—Pattern reduction enhanced ant colony algorithm; clustering; optimization

I. INTRODUCTION

Clustering means group the data naturally. From a set of data categorized into clusters based on similarities or differences in the features of each data. Clustering methods perform unsupervised clustering of the data. Grouping the data by its nature is divided into two categories, soft and hard clustering. Soft clustering classifying each data into more than one cluster. Hard clustering classifying each data exactly one cluster data.

There are some method of developing cluster analysis. One of these studies is on hard clustering. Some of these methods are K-Means, SOM, G-Means, X-Means [1]. Each of these methods succeeded in grouping. Based on the K-Mean by Gath and Geva [2] developed a method combining fuzzy clustering and fuzzy c-mean maximum likelihood to determine the number of clusters automatically. By [3] proposed a fuzzy clustering method to determine the number of clusters dynamically. Another method in hard clustering are SOM and DBSCAN.

The method for clustering the data naturally have various problems. One of the problems can not determine the degree of membership of each group of data. However, method that has been developed indicates the distance information can determine the degree of similarity between data. The next major issue is time computation, and the rate of convergence.

Ant Colony Optimization is a method of viewing and imitating the behavior of ants [4]. This optimization method is used to increase the performance of K-Means clustering method. This method is used in clustering and did well. Because they are new, the ant colony optimization for clustering needs development. By [5] developed this method and produce better quality data clustering.

Ant colony optimization method for clustering have limitations. The following limitations computing time high, a variety of parameters, the degree of convergence, and the results of clustering data. [6] successfully developed ant colony optimization (ACO) method produces better clustering, but has high computational time and requires the evaluation function. By [7] managed to improve the performance of ant colony optimization method for clustering, but it has limitations that have high computing time.

Pattern reduction enhanced ant colony optimization (PREACO) developed for the case of codebook generation succeeded in improving the performance of ACO with faster computation time. This method seeks to reduce redundancy selection solution by ant agents.

Based on [8] research, we propose that method for clustering and analyzing the results. This method produces a solution with reduced redundancy selection agent solutions for ants. This function ensures the new pheromone has a maximum value, with this pheromone as guidance for the next ant agents to choose the solution.

The remainder of this study is organized as follows. Section 1 briefly gives the necessary background for this study. Section 2 presents the proposed PREACO algorithm to solve the problem of section 1. Sections 3 respectively give the experiment results for the six benchmark data sets and the model evaluation results. Finally, concluding remarks are made in Section 4.

II. Ant Colony Optimization for Clustering

Clustering map the data set into k cluster group. The process of collecting data in a cluster based on the similarities between the euclidean distance data. Clustering data can be separated properly if the distance between cluster centers farther. the mathematical formulation of clustering data is presented in (1).

$$\text{Min } F(w,m) = \sum_{j=1}^{K}\sum_{i=1}^{N}\sum_{v=1}^{n} w_{ij}\left\|x_{iv} - m_{jv}\right\|^2 \quad (1)$$

Where, j, K is cluster number; i, N is point data; and v, n is attribute of data.

Objective function value (F) is obtained by calculating the distance between the data points (X_{iv}) and the cluster center (m_{jv}). The distance value multiplied by the weight (w_{ij}) that was formed before. The objective function indicates the value of the solution that has been created.

The weight values obtained from solutions that have been formed. weights indicate that the data included in a cluster. Weights will be set to 1 if the data included in the cluster to j (2), otherwise the value is 0.

$$w_{ij} = \begin{cases} 1, if\_element\_i\_include\_cluster\_j \\ 0, otherwise \end{cases} \quad (2)$$

Where, (w_{ij}) is weight of point data i in cluster j.

Matrix cluster centers using a weight values. As well as the average value, a value of center cluster has the same analogy. Multiplying weight with the data and divided by the sum of weights in the same cluster, so that we will get the new value of the cluster center (3)

$$m_{jv} = \frac{\sum_{i=1}^{N} w_{ij}x_{iv}}{\sum_{i=1}^{N} w_{ij}}, j = 1,...,K\_and\_v = 1,...,n \quad (3)$$

Where, j, k are number of cluster; v, n are number of attribute; i, N are number of point data. Also, m_{jv} is variable to save center cluster of cluster j of attribute v. Next variable is (w_{ij}) this refers to weight of point data i in cluster j, where x_{iv} is attribute of point data i in attribute v. Matrix will be made by size K x N.

Methods are based on a number of R ant agent to find a solution. The process of finding a solution, and updates the weighting of repeated cluster center based on the number of ant agents that have been defined. Solutions that are created as much R ant agent.

Solution created is determined by the objective function. The quality of a solution is calculated based on a value of the objective function. the smaller value of the objective function, then the solution is better. Therefore, the solution will be sorted by the objective function sequences from small to large.

Selected solutions updated with local search formula. The expectation of data clustering solutions become even better. The next step is to calculate the pheromone. Pheromone that has been created then updated based on (5). This process is repeated until the number of iterations.

A. Generate Population

Ant Colony Optimization [6][7][8] method has the ability to optimization can also map data into the appropriate cluster. So the data with similar features will be entered into the same cluster otherwise enter a different cluster. To do that, the solutions produced by the ACO method. The description of solution is along the amount of data as in table I. The column contains the number of cluster.

Each R agent represents a solution that is created. Initially the solution is empty. So that each ant will bring an empty solution, and will be filled when the ACO process is running. Ants will map each data into appropriate clusters to be stored on a matrix solution. One solution contains a cluster numbers. The solution has a length of N data. And matrix solution has a size matrix R x N solution. That means the matrix solution has R rows and N number of columns solutions plus one column for its objective function (OF).

TABLE I. Solution Interpreation

	Data							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Cluster	2	1	3	2	2	3	2	1

B. Solution Construction

One of the functions in the ACO method is *Soluction Construction()* or build solutions. This function is to reconstruct or build a path to a food source or analogous to defining the solution of a problem based on the pheromone trail and information. Each individual (ant) look for food sources from lane to lane until all channels exceeded. This picture shows the possibility or probability of the solution, as shown in (1). Where d is representing the pheromone and the heuristic information, and e is the path of the ants. Basically heuristic information can be assumed to be the inverse of distance or in terms = 1 / d, where d is the Euclidean distance formula of data against centroid in the same cluster. Steps that must be done is to send individual ants in conducting random searches of food sources, according to (4) from [6].

$$s = \begin{cases} \arg\max_{j\in K}\{\tau_{ij}\cdot[\eta_{ij}]^{\beta}\}, if\_q \le q0 \\ J, Jika\_lainnya \end{cases} \quad (4)$$

Where, s is solution of cluster that choose. Variable q and $q0$ is random number and number who determines manually 0.98 for example. J is probability methods to choose cluster. Then, $_{j\in K}\{\tau_{ij}\cdot[\eta_{ij}]^{\beta}\}$ refers to multiply pheromone value τ_{ij} of point data i and cluster j, and $[\eta_{ij}]$ is heuristic information value or distance. Where, j is cluster of number cluster (K).

C. Update the Pheromone

Pheromone update function is required to perform an update of pheromone left by individuals or ant agents. It is associated as the search experience of ant agents to find solutions. Each pheromone left as the trail will be chosen by the individual ant further, more individual the same choice of the trail, the probability of a solution on the line increases. This can be seen in (5) from [6].

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{l=1}^{L} \Delta\tau_{ij}^{l} \quad (5)$$

$i = 1,..., N; j = 1,..., K$

Where, i, N is point data number and j, K is cluster number.

New pheromones ($\tau_{ij}(t+1)$) are calculated using the evaporation rate $(1-\rho)$ and ($\sum_{l=1}^{L} \Delta\tau_{ij}^{l}$) can change by the value of the objective function (*OF*) of the solution. Value is equal to 1 / *OF* for the data included in the cluster. While the evaporation rate can be calculated by the 1-ρ. A value of 1 / *OF* is used to improve pheromones, it will get a clue to the next ant in building solutions.

D. Pattern Reduction Enhanced Ant Colony Optimization

PREACO is a method based on ant colony optimization (ACO). This method was introduced by [8]. Basically, this method combines pattern reduction (*PR*) into the ACO in order to run properly and quickly. Therefore, the method of ACO given an additional function. As seen in the following algorithm:

Algorithm 1 PREACO:

1. Initialization ()
2. While the termination criterion is not met
3. s = SolutionConstruction ()
4. τ = PheromoneUpdate ()
5. PatternReduction (s)
6. LocalSearch (s)
7. End
8. Results.

For the first step in the algorithm in step 1 to 4 and step 6 up to step 8 is a pure ACO algorithm. In step 5 is the addition of side PREACO to reduce redundant (repetition of the process) and look for the right pheromone. Because redundant in search of food sources on by ants often repeated, so it will take a lot of time. With the addition of these can be maximized.

In step 5 explains the functions of which there are various benefits. In Patternreduction there are three processes, namely the detection, compression, and removal. This is done to detect the maximum path selection, while compression and removal finding and eliminating step path selection algorithm which is less than the maximum in order to optimize and save time and on target.

Besides, a detailed explanation can be seen in the following pseudocode describing the detection operator [8]. This operator serves to maximize the detection of ant paths in the search for food sources. It is also part of Patternreduction.

Algorithm 2 detection operation [8]:

1. / * *Keep the number of times of ants passing lane* * /
2. **For** k = 1 to / * *is the number of individual ants* * /
3. **For** i = 1 to n / * *n is the number of lines* * /
4. $v_{i,s_i^k} \leftarrow v_{i,s_i^k} + 1$ / * *v is an array to store the number of times the path is exceeded* * /
5. **End**
6. **End**
7. / * *Determining the quality level of convergence or when roaming* * /
8. **For** each edge
9. If $v_{ij} \geq \psi$
10. $\zeta_{ij} \leftarrow 1$ / * *array keeps track of the elapsed time and the ants in particular iteration* * /
11. **End**
12. **End**

The second part of this Patternreduction can be seen in algorithm of PREACO will ensure the selection of ants in an ant or a path in order to stay on the right track. This algorithm tell us to keep tracks of agent of ants that already assign. If the iteration have number more than threshold (ψ) than pheromone value will be assign as 1. Threshold value has gotten by multiply $\psi = \varrho * \theta * \lambda$. This ϱ means number of iteration, say every 10 iteration. This simbol (θ) means number of agents of ants. Last simbol (λ) means percent of number of agents that already determines by manual. For example, ϱ=10; θ=10; λ=4 / 100 * 10, so threshold value (ψ) = 10 * 10 * 0,4 = 40. So, if the iteration already reach 40 than value of pheromone of solutions of point data will be set by 1. In terms of the edge (line) that has been selected by other ants and have reached the maximum track it will be given priority and the next so that the ants can follow this path. With so the path has been passed does not need to be checked again, pretty lines with high priority are skipped the individual ants.

III. EXPERIMENT

These experiments trying to find the exact value of the various parameters that are used as a reference for testing. ACO parameters for clustering have a number of iterations, agents, *q0*, evaporation rate, *K*, and sigma. These parameters will determine the solution to be evaluated using the *SSE* (6) and *OF* values and calculated computing time.

$$SSE = \sum_{i=1}^{K} \sum_{x \in C_i} (x - m_i)^2 \quad (6)$$

Where, i,K number cluster; x, C is point data that element of cluster. Then, m_i is center cluster of the cluster.

The experiments were performed on multiple datasets and several different methods. With the parameters of the various methods is aimed to obtain precise parameter values at each method with the best results. The best solution when the value of *SSE* is small with a little time. Set of parameters to be sorted by the value of the smallest *SSE*. This is necessary because, the value of *SSE* is a method to assess how close the relation between data in the same cluster.

A. Data set

The dataset used in this study are data iris, wine, and T4 (Table II). Data iris and wine are often used in the same method on previous research.

TABLE II. DATASET DESCRIPTION

Data Set	Number of Data	Number of *Cluster*(K)	Number of Attribute
Iris	150	3	4
Wine	178	3	13
T4	400	5	2

Iris datasets in Table II have the following criteria. Data with a total of 150. It has a number of K (Cluster) = 3, Number of attributes = 4. Data are sorted from 1 to 50 as a data cluster 1, the data to-51 to-100 data to the cluster 2, and the rest is up to 150 as a cluster 3. Data retrieved and downloaded from the website UCI datasets.

Wine datasets require data normalization. In this data has a very high diversity among attributes, thus requiring data normalization. Data normalization using the normalization min max (4). To do this normalization is done on Microsoft Excel application software. The character of wine consists of a cluster 1 = 59 data points, 71 data points for cluster 2, and 48 data points for cluster 3. Data has been sorted from cluster 1 to cluster 3. Data obtained from the site UCI datasets.

$$New\_VAlue = \frac{Original\_Value - Min\_Of\_Original\_Value}{Max\_Of\_Original\_Value - Min\_Of\_Original\_Value} \quad (4)$$

Where, *new_value* is result of the pattern or some new value. *Original_value* is original value from wine dataset. *Min_of_originial_value* is minimum value of wine dataset. *Max_of_original_value* is maximum value of wine dataset.

While T4 datasets is come from our previous research. This datasets is data synthesis, it has 400 data points. The data is sorted from cluster 1 to cluster 5. Each cluster has 80 data points.

B. Parameter Experiment

This part tell us about result of parameter experiment. PREACO is implemented and tested to all of the dataset. In these experiment we will get good criteria to produce correct solutions.

In Table III illustrates the experimental results search parameters to methods ACO on iris dataset. On the table has been sorted by the smallest value of the *SSE*. Letters in bold are the parameters to be used in this method.

Table IV describes the results of experimental parameters on Wine datasets. On the table has been sorted by the value of *SSE* and the shortest time. Unlike the experiment in Iris, Wine has a relatively longer time. This happens due to the amount of Wine datasets more than Iris.

Table V describes the experimental results of searching parameters on T4 datasets. The table has been sorted by the value of *SSE*. And selection of parameters based on the value of *SSE* small and shortest time.

C. Accuracy

To obtain a good performance of the algorithm necessary to test the accuracy (7) of the method. This is done by calculating the correct number of clusters that already formed compare to the number of total cluster. In addition, to testing the proposed method the evaluation between methods is needed.

Table VI and VII describe us result of the experiment of the method's performance. Process to get data of that table is come from ACO and PREACO clustering. First process is done to Iris datasets. The result that process there are 16 point data of wrong cluster than PREACO has 15 point data of wrong cluster. Second process is done to Wine datasets. The result has 17 point data of wrong cluster of ACO and 27 point data of wrong cluster of PREACO. Third process is done to T4 datasets. The result has 115 point data of wrong cluster of ACO and 125 point data of wrong cluster of PREACO.

The result in table VII illustrates the computation time of method to do clustering data. This computation time calculated by function program of java programming during process. The result of experiment for iris dataset show that ACO method need 73 second, and 46 second for PREACO method. The result for wine dataset show that ACO method need 272 second, and 141 second for PREACO method. The result for T4 dataset show that ACO method need 204 second, and 150 second for PREACO method.

Table VI describe that the proposed method(PREACO) better in some data and worse in another. But table VII describe about superior the method (PREACO) based on time computation to ACO.

$$\text{Accuracy} = \frac{Number\_Of\_Correct\_Cluster}{Amount\_All\_Of\_Cluster} \quad (7)$$

Where, Accuracy come from devide number of correct cluster in solution by amount all of cluster.

TABLE III. BEST PARAMETER TEST FOR IRIS DATA

Time(s)	SSE	OF	Iteration	Agen	q0	eva	sig
57	14.58	92.94	2000	40	0.90	0.10	2
24	**15.02**	**96.05**	**800**	**40**	**0.90**	**0.10**	**2**
56	15.05	95.46	2000	40	0.90	0.10	2
28	15.06	97.01	900	40	0.85	0.10	2
21	15.11	96.78	700	40	0.75	0.10	2
14	25.42	207.05	700	30	0.98	0.01	2
21	25.44	198.79	700	40	0.98	0.01	2
21	25.70	180.88	700	40	0.80	0.01	2
21	25.81	223.33	700	40	0.98	0.01	2
9	25.83	212.45	700	20	0.98	0.01	2

TABLE IV. BEST PARAMETER TEST FOR WINE DATA

Time(s)	SSE	OF	Iteration	Agen	q0	Eva	sig
131	11.84	87.49	2000	20	0.75	0.1	0.9
196	11.95	87.93	2000	30	0.80	0.1	1.1
131	12.03	88.23	2000	20	0.75	0.1	1.1
131	12.13	88.45	2000	20	0.80	0.1	1.1
133	12.14	88.46	2000	20	0.75	0.1	2.0
116	12.14	90.21	900	40	0.80	0.1	1.1
78	12.33	93.62	600	40	0.80	0.1	1.1
89	12.46	103.41	700	40	0.90	0.1	1.1
96	12.47	94.24	1000	30	0.85	0.1	1.1
64	12.55	92.77	1000	20	0.90	0.1	1.1
67	12.69	96.23	700	30	0.90	0.1	1.1
89	12.85	103.37	700	40	0.90	0.1	2.0
77	12.91	99.99	600	40	0.90	0.1	1.1
44	**13.03**	**102.18**	**700**	**20**	**0.90**	**0.1**	**1.1**
116	13.04	101.15	900	40	0.80	0.1	2.0
116	13.16	105.34	900	40	0.80	0.1	0.9
96	13.16	99.86	1000	30	0.80	0.1	1.1
78	13.22	104.31	600	40	0.85	0.1	1.1

TABLE V. BEST PARAMETER TEST FOR T4 DATA

Time(s)	SSE	OF	Iteration	Agen	q0	Eva	sig
90	10.28	91.29	900	40	0.90	0.10	1.1
90	10.45	146.47	900	30	0.98	0.01	1.1
95	10.55	94.22	1000	40	0.90	0.10	2.0
74	10.70	142.44	1000	30	0.98	0.01	1.1
89	10.73	143.48	900	40	0.98	0.01	2.0
96	10.73	89.45	1000	40	0.85	0.10	2.0
78	10.76	93.69	900	30	0.85	0.10	2.0
97	11.04	89.97	1000	40	0.80	0.10	2.0
94	11.14	143.49	900	30	0.98	0.01	2.0
119	11.24	98.30	900	40	0.85	0.10	2.0
85	11.34	98.32	1000	30	0.85	0.10	2.0
76	11.36	105.57	1000	30	0.90	0.10	2.0
87	11.37	99.75	900	40	0.90	0.10	2.0
75	11.44	142.40	1000	30	0.98	0.01	2.0
27	**11.52**	**151.80**	**600**	**20**	**0.98**	**0.00**	**2.0**
72	11.52	102.22	900	30	0.90	0.10	1.1
88	11.61	101.25	900	40	0.98	0.10	1.1
97	11.64	92.13	1000	40	0.80	0.10	2.0
45	11.65	100.61	900	20	0.75	0.10	2.0
78	11.66	97.01	1000	30	0.85	0.10	1,1

TABLE VI. ACCURACY FOR PREACO AND ACO

DATA SET	Algorithm	
	ACO	PREACO
Iris	89.30%	90%
Wine	89.90%	85%
T4	70.80%	68.80%

TABLE VII. TIME COMPUTATION FOR PREACO AND ACO

DATA SET	Algorithm	
	ACO(s)	PREACO(s)
Iris	73	46
Wine	272	141
T4	204	150

D. *Analysis*

To understand the performance of the algorithm need to compare PREACO and ACO in time computation also about the algorithm experiment itself.

Time computation can reduce well that we can see in table VII. It describes about use of PREACO specially for detection algorithm. Because, if ACO can do convergence in some period. But use detection operation algorithm can convergence in less period, it can happen because of the redundance of choosing solution has already decrease by threshold. Value of $\zeta_{ij} \leftarrow 1$ show that pheromone will be set to maximum, so another process no need to repeat. The next agent of ant will choose the same solution that already define by another agent in past. With that process, the redundancy automatically erase. It means, time computation also decrease.

Another analysis of best parameter of PREACO. In past research, there are some parameter that already use in ACO, because we use PREACO so we need to test that parameter in PREACO. This result show in table III to V, and font that write in bold is the best parameter we choose. The choosen based on Sum of Squared Error and best time computation. We need to do this, because we need to make sure that best parameter in ACO also be the best parameter in PREACO.

Finally, in table VI tell us about the result of the method performance. PREACO and ACO need to compare beside time computation also in accuracy of data clustering.

IV. CONCLUSION

Pattern Reduction Enhanced Ant Colony Optimization to solve clustering problem has been use and tested in this paper. The ant agent use pheromone and pattern reduction to make sure value of the pheromone still high. The use of this pheromone kind of adaptive memory to guide another ants towards the optimal clustering solution. And the use of pattern reduction to cut redundancy loop for the process. The algorithm has already implemented and tested to some dataset and compare it to Ant Colony Optimization. Basically this method work well to clustering same as ACO did although has some limitations in accuracy especially in data wine and T4, it needs to do next research. But for time computation, PREACO looks superior to ACO on all of the dataset. The test results show that the proposed method has 46 second faster than ACO method (73 second) for iris dataset, 141 second faster than ACO method (272 second) for wine dataset, and 150 second faster than ACO method (204 second) for synthetic dataset.

This research has already determine examine exact parameter for PREACO clustering.

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