IJESRT

INTERNATIONAL JOURNAL OF ENGINEERING SCIENCES & RESEARCH TECHNOLOGY

Image Cluster Based On Precedence Pheromone Algorithm

S.Venkateshkumar[*1], Dr SNS Rajalakshmi[2]

[*1]Research Scholar, Department of MCA, Manonmaniam Sundaranar University, India

[2]College of Arts and Science, Coimbatore, Tamilnadu, India

gowthamvenkyy@gmail.com

Abstract

Various Swarm Intelligence algorithms have been urbanized to solve numerical and combinatorial problems. Clustering difficulty has been approached from different disciplines. This paper introduces a new algorithm called Priority Based Pheromone Algorithm (PBPA) belongs to Ant colony System to give better optimal solution for clustering. Concept of this algorithm is to built clusters using three potential values priority value, pheromone and heuristic information. This algorithm is compared with normal Ant colony algorithm, Genetic Algorithm and basic K-means algorithm. Comparison done by percentage of errors, best fitness(time efficiency) and maximum number of iterations. As compared with above said algorithms, proposed method shows better results. Clustering with swarm-based algorithms especially Ant colony algorithm is have been shown better results in a variety of real world application.

Keywords: component: Swarm Intelligence and Data Mining Ant Colony Algorithm, Clustering, Image data set,.

Introduction

Amid considerable turn down in data storage expenditure, swift improvement in computer networks, technology advances in data acquisition, development in computer performance and volatile growth in the generation of electronic information, enormous quantity of data are being composed and stored in databases. It is thus no trouble-free matter to discover business intelligence that must help decision making. Hence, for such large data base have led to the emergence of a field called data mining. Data Mining refers extract hidden knowledge from large amounts of data. This encompasses a number of technical approaches such as clustering, data summarization, classification, finding dependency networks, regression, analyzing changes and detecting anomalies. Cluster analysis is the task of partitioning data sets into clusters with general similarity so that a data element shares additional similarities with its member set rather than any other group.

A extremely vital step in this digital information processing is to group the data in some approach so that patterns can be recognized. Clustering can be used for this task. In the medical field, clustering of data can be used to determine if a medicine provides greater benefits to a certain group of patients.

Grouping of information is used in the engineering field to determine what factors lead to the failure of a component in a system 7]. And in marketing, data clustering can give a clearer picture of how to focus an advertising operation to the proper audience. The concept of clustering has been around for a elongated time. It has several applications, particularly in the context of information retrieval and in organizing web resources. The main purpose of clustering is to locate information and in the present day context, to locate most relevant electronic resources [3].

Diversity of approaches is implemented to define optimizing clusters, including swarm intelligence. One of the famous algorithm in swarm intelligence is applied here called Priority Based Pheromone Algorithm(PBPA) which is belongs to Ant Colony Algorithm. Remaining section will be discussed by following: In section II describes associated work, in section III detail explain Priority based algorithm, IV section Pheromone Management V section Experimental Analysis will be discuss and in section VI grasp conclusion.

Associated Work

Several algorithms have been proposed in the literature for clustering [8]. Studies of the social behavior of organisms (individuals) in swarm prompted the design of very efficient optimization and clustering algorithms[9][10]. Algorithms based on the basic model include an application to customer clustering analysis by Dai *et al.* [11] and the Improved Ant Colony Clustering (IACC) algorithm by Jiang *et al.* [12].ACO approach was proposed in 1992 by Marco Dorigo et al. to solve several discrete optimization problems [13] [14][15]. Manfrin *et al.* used parallel implementations of ACO [16], [17]. ACO has been applied to classification problems, as shown by Parpinelli *et al*. in the AntMiner algorithm [18], [19].

Clustering have develop into a widely deliberate problem in a variety of application domains, such as in data mining and knowledge discovery [1], [2] statistical data analysis [3], [4] data classification and compression [6], medical image processing [5] and bioinformatics [6]. Kaiguo Fan & Jianguo Yang & Hui Jiang &Wei Wang & Xiaodong Yao discussed how to recover errors in clusters[27]. The AntMiner algorithm was used by a number of other researchers, such as Ji *et al.* in a sequential covering approach to discover a list of classification rules covering all training cases used [20]. and Moayed for web page classification [21]. Michelakos *et al. used* cAnt-Miner2 to extend the approach to coping with continuous attributes, a superior process to the cAnt-Miner method [23]. Other data mining applications include an approach by Zhu *et al*. where they apply a discretization algorithm based on an information-distance criterion and ACO for knowledge extraction on an industrial database [24]. The next section looks at how ACO has been adapted for clustering problems.

Precedence Based Pheromone

The basic idea of ACO is to simulate the foraging behavior of ant colonies. When an ants groups try to search for the food, they use a special kind of chemical to communicate with each other. That chemical is referred to as pheromone. Initially ants start search their foods randomly. Once the ants find a path to food source, they leave pheromone on the path. An ant can follow the trails of the other ants to the food source by sensing pheromone on the ground,. As this process continues, most of the ants attract to choose the shortest path as there have been a huge amount of pheromones accumulated on this path. This collective pheromone depositing and pheromone following behavior of ants becomes the inspiring source of ACO. In this paper we introduce a new type of Ant Colony Clustering called precedence Based Pheromone Algorithm(PBPA) to tackle the clustering problems in Data Mining. It is similar to Ant Colony but has three major difference. Firstly, PBPA uses priority table system and secondly, it allows ant to detect path by using priority value, pheromone information and heuristic value and thirdly, each ant have the search information used to detect feature combinations. Algorithm can be viewed as the interplay of the following procedures.

- *Initialization of algorithm:* All pheromone values and parameters are initialized at the beginning of the algorithm.
- *Initialization of ants:* A group of N artificial ants are initialised to N number of objects.Each ant contains priority table to maintain information of objects and other ants. In each iteration, initially each ant randomly selects a constructive direction .
- *Local Pheromone Updating:* quickly after if an ant A_i met a matched object M_j ,the corresponding pheromone value is updated by a local pheromone value.
- *Proirity Value Updating:* If an ant A_i met a new ant A_j, it share the priority table information of matched and unmatched object and its priority value is updated by priority value updating rule.
- *Cluster Construction:* N ants set out to found path to N objects based on priority value, pheromone value and heuristic information using the construction rule of PBPA algorithm.
- *Global Pheromone Updating:* N ants build solution to C clusters at the end of each iterations ,pheromone values are updated by global pheromone value to get best solution.
- *Fitness Solution:* At the end of iteration find the best solution from the result of completed iterations.

A. Priority Table Information

In this paper we newly introduce a priority table to Ant Colony Algorithm called Priority Based Pheromone Algorithm(PBPA). Priority table are initialised at start of this algorithm. The domain define set of objects which are distributed in multidimensional space with specific values for reference. Ants are located at each object and start searching randomly. Initially all values in a table are empty. When two ants meet at in a searching space it share a priority table values and update its table as per sharing information. Here each ant make up priority table that hold three major columns: Visited Object, Unvisit Object and Visited Ant. Visited Ant (Va_i, where i=1,2,…N) hold information about already visited ants so it prevent ants from discussion about priority table and it save time. Remaining two of this column are described below briefly as:

I. ***Visited Object-*** Ants in search space frequently visiting objects and in needs to store information of this object for feature reference. So this column is utilised as multipurpose by an ant to complete its search and for feature combinations. This column contains matched and unmatch section. Here each ant start searching objects randomly, and it visit both matched and unmatched object. When two ants meet, it overlap information of visited objects and both of them update its matched and unmatch column. So entire ants remember the visiting objects and prevent it from repeaitition.Visited Object is noted by Vo_i^j, means i^{th} ant $(1 \leq i \leq N)$ visited j number of objects where j=1,2,…N and matched object denoted by M_i^k, means i^{th} ant visited k^{th} object where k=1,2,…j and Unmatch object is denoted by U_i^k, means i^{th} ant visited unmatch k^{th} object .

II. ***Unvisit Object***- In this column each ant hold information about unvisited object and it contain two section match and unmatch that similar to visited object. After updating its priority table ant arrange the match column values in increasing order and it give preferrence by top to bottom value. So every ants recognize to claim most required object in searching space. Unmatch column value are utilize for feature search. In search space ant meet happen n number of times and each it update and order the match table so it reduce the overall searching time.Unvisit object is denoted by Uo_i^l,means i^{th} ant$(1 \leq i \leq N)$ need to visit l number of objects in search space where l=1,2,…N-j and after increasing order matched object referred as M_i^k , means i^{th} ant give first preference to k^{th} object where k=1,2…l and Unmatch object noted as U_i^k, means i^{th} need to visit at last of k^{th} unmatch object. The flow chart of this algorithm are given in fig.1 Procedures of this algorithm are detailed briefly in remaining section.

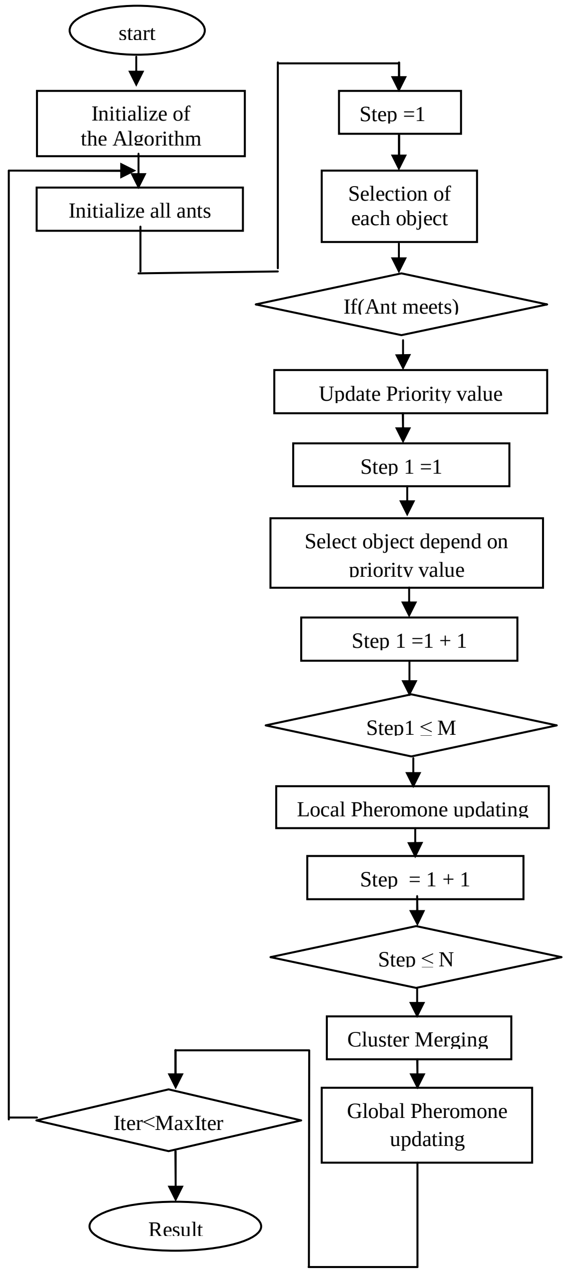


Figure 1. Flow chart for Priority Based Pheromone Algorithm(PBPA)

B. Pheromone and Heuristic Information

Pheromone is some kind of chemical released by ant while searching for food. In general pheromone is used to record the searching experience in ants behavior. Heuristic refered as some method based values used to guide ants search direction in multi dimensional space. As the clustering problem is mainly group the matching object in a searching space. Here, we denote the pheromone value as τ_i^j

when A_i^j to i^{th} Object O_i and heuristic information value of mapping A_i^j to O_i as η_i^j.

i) Ant states depend on priority and pheromone deposition

An ant can be in six states as mentioned below:

a) State S1: Initial

Initial state will appear only at the starting of each iteration. In this states N ants and N priority tables to each ants are initialized and start searching randomly. Pheromone and heuristic helps ants to find path in hyperspace. At the beginning of algorithm, we set all pheromone values to an initial value τ_0 as

$$\tau_i^j = \tau_0 , \quad 1 \leq i \leq N \text{ and } 1 \leq j \leq N; \qquad (1)$$

As, moreover M number of clusteres with different characteristic are found by ant at the end.Pheromone values follow same methods updation for both local and global atall states that will be defined next section but for heuristic different methods are insisted at diferent states.

b) Heuristic A: S1

In Initial state heuristic biasis the ants to select the starting object with randomly. Heuristic of state S1 is denoted by AS1.Suppose that an ants heuristic type is in initial ,then the heuristic value of searching A_i^j to O_i denoted by

$$\mathrm{AS1} = \eta_i^j = \frac{A_i^j.o_j - \mathrm{Min\_length}}{\mathrm{Max\_lengh} - \mathrm{Min\_length}} + 1 \qquad (2)$$

where, $\mathrm{Max_lengh} = \max_{1 \leq j \leq o_j}\{A_i^j.o_j\}$and $\mathrm{Min\_lengh} = \min_{1 \leq j \leq o_j}\{A_i^j.o_j\}$. According to above equation an object with higher value will be associated with higher heuristic value and it also confirms that η_i^j is normalised with interval(0,1). The reason to add 1 in both numerator and denominator is to prevent from zero divided.

c) State S2: Search, deposit and update

In this state ant perform three function searching, depositing and updating. Ants searching objects in space and if found matching objects it deposit pheromone on searching path and update its matched object within visited object in priority table.

d) Heuristic B: S2

Heurictic value of this state is denoted by BS2 and this state heuristic bias the artificial ants to select an match object. Suppose that ants heuristic state in search,deposit and update, then heuristic value of A_i^j searching to O_i and found that as match object M_i^k then

$$\mathrm{BS2} = \eta_i^j = \frac{\mathrm{Max}\{M_i^k(\mathrm{Vo}_i^j)\} - A_i^j}{\mathrm{Max}\{M_i^k(\mathrm{Vo}_i^j)\} - \mathrm{Min}\{M_i^k(\mathrm{Vo}_i^j)\}} + 1 \qquad (3)$$

where, $\mathrm{Max}\{M_i^k(\mathrm{Vo}_i^j)\}$ is maximum match value in Visited object and $\mathrm{Min}\{M_i^k(\mathrm{Vo}_i^j)\}$ is minimum match value in visited object. According to this an higher reliability of match object will be associated with higher heuristic value and it also specifies that η_i^j will be two values as (0,1).

e) State S3: Search and update

In state 3 ant performs only two functions searching and updating. It move directly to next object without leave pheromone which visit unmatched object and update its priority table in unmatched object within its priority table. Pheromone for this state is generated but when ants found that visiting object is an unmatch object then pheromone value of τ_i^j will become zero.

f) Heuristic C: S3

In this state heuristic bias the artificial ants to select an object with higher reliability. Suppose that ants heuristic type is search and update, and it found unmatch value in visited object, then the heuristic value of searching O_i with A_i^j by

$$\mathrm{CS3} = \eta_i^j = \frac{\mathrm{Max}\{U_i^k(\mathrm{Vo}_i^j)\} - A_i^j}{\mathrm{Max}\{U_i^k(\mathrm{Vo}_i^j)\} - \mathrm{Min}\{U_i^k(\mathrm{Vo}_i^j)\}} + 1 \qquad (4)$$

where, $\mathrm{Max}\{U_i^k(\mathrm{Vo}_i^j)\}$ is maximum unmatched value in Visited object and $\mathrm{Min}\{U_i^k(\mathrm{Vo}_i^j)\}$ is minimum unmatched value in visited object. According to this an higher value of unmatched object will be associated with higher heuristic value and it also confirm that η_i^j values in (0,1).

g) State S4: Follow path and update

In state 4 ants perform two action follow the path that is visited by ants in search space and updating its priority table. Here, ant in S3 found a pheromone trace and start searching and update its unmatched object within unvisit object in priority table. In this state ant does not leave pheromone for unmatch object. Pheromone value for this state is generated but when an ants found that unvisiting object is an unmatch value then pheromone value of τ_i^j will become zero.

h) Heuristic D: S4

Heuristic value of this state is noted by DS4. In this ants heuristic type is follow up and update as well as ants found an unmatch value in unvisited object then heuristic value of A_i^j denoted by

$$DS4 = \eta_i^j = \frac{Max\{U_i^k(Uo_i^l)\} - A_i^j}{Max\{U_i^k(Uo_i^l)\} - Min\{U_i^k(Uo_i^l)\}} + 1 \quad (5)$$

where $Max\{U_i^k(Uo_i^l)\}$ is maximum unmatch value in unvisited object and $Min\{U_i^k(Uo_i^l)\}$ is minimum unmatch value in unvisited object. It shows the value of η_i^j will be 0 or 1.

i) State S5: Follow path, deposit and update

Ant in state 5 perform three action as following the trial path at the same time depositing pheromone on ground as well as updating its priority table. In this ant in S2 found a pheromone path and follow it at the same time deposit pheromone on ground when it is an matching object and update its priority table column matched within unvisited object.

j) Heuristic E: S5

Heuristic value of this state is called by ES5. Suppose ants heuristic type is follow up ,deposit and update as well as ants found an match value in unvisited object then heuristic value of A_i^j is denoted by

$$ES5 = \eta_i^j = \frac{Max\{M_i^k(Uo_i^l)\} - A_i^j}{Max\{M_i^k(Uo_i^l)\} - Min\{M_i^k(Uo_i^l)\}} + 1 \quad (6)$$

where $Max\{M_i^k(Uo_i^l)\}$ is maximum match value in unvisited object and $Min\{M_i^k(Uo_i^l)\}$ is minimum match value in unvisited object. The heuristic value of η_i^j is either 0 or 1.

k) State S6: Only Update

Ants falls in this state when two ants meet in a multi dimensional search space. This is only state ant does not use pheromone and heuristic value. Once ant meet happen first it check whether this ant is already met or not using ant seen column. If it is already met this ant both of them say thanks and start searching next object. If not then share information of visited and unvisited object. First ant look into second ant visited object column, and it helpful the first ant to know the path of any unvisited object. Similarly second ant look visited object column in first ant table. It update only unvisited object column and it does not touch visited object column, it use this column only for its reference purpose. It use different method to update match and unmatched value in unvisited object column for both it use average value described below:

$$Avg(M_i^k) = \frac{\left(Min_{\forall o_j} \epsilon Succ(o_j)\{M_i^k(Uo_i^l)\}\right) - \left(Min_{\forall o_j} \epsilon Prec(o_j)\{M_i^k(Uo_i^l)\}\right)}{2} \quad (7)$$

$$Avg(U_i^k) = \frac{\left(Min_{\forall o_j} \epsilon Succ(o_j)\{U_i^k(Uo_i^l)\}\right) - \left(Min_{\forall o_j} \epsilon Prec(o_j)\{U_i^k(Uo_i^l)\}\right)}{2} \quad (8)$$

Here, $Avg(M_i^k)$ and $Avg(U_i^k)$ is average value of matching object and average value of unmatch object in unvisite object column.Where $Min_{\forall o_j} \epsilon Succ(o_j)\{M_i^k(Uo_i^l)\}$ it means get the minimum value fron first half of the matching value in unvisited object and $Min_{\forall o_j} \epsilon Prec(o_j)\{M_i^k(Uo_i^l)\}$ means get next minimum from second half of the matching value in unvisited object.Similarly $Min_{\forall o_j} \epsilon Succ(o_j)\{U_i^k(Uo_i^l)\}$

means minimum of first half unmatch value and $Min_{\forall o_j} \epsilon Prec(o_j)\{U_i^k(Uo_i^l)\}$ is minimum second half unmatch value.

$$\delta_i^j(M_i^k) = \frac{Max\{|M_i^k(Uo_i^l) - Avg(M_i^k)|, |Avg(M_i^k) - M_i^k(Uo_i^l)|\}}{Avg(M_i^k)} \quad (9)$$

$$\delta_i^j(U_i^k) = \frac{Max\{|U_i^k(Uo_i^l) - Avg(U_i^k)|, |Avg(U_i^k) - M_i^k(Uo_i^l)|\}}{Avg(U_i^k)} \quad (10)$$

Here, $\delta_i^j(M_i^k)$ and $\delta_i^j(U_i^k)$ is priority value of matching and unmatching value in unvisite object.. This priority value of each match and unmatch object will arrange by increasing order and ant use this for searching.Using above Match and Unmatch column in priority table has been updated.

Pheromone Management

A) Pheromone Initialization

Starting stage of each iteration, all pheromone values are initially set to τ_0 .This τ_0 is the minimum value of all pheromone values which is given by the following equation: where, Min_Objectvalue and Max_Objectvalue is the minimum and maximum value of searching object in multi dimensional hyper space.

$$\tau_0 = \frac{Min\_Objectvalue}{Max\_Objectvalue} \quad (11)$$

B) Local Pheromone updating

After each ant found object in search space o_j by A_i^j , the local pheromone updating rule is applied to attraction o_j for later ants. The local pheromone updating rule is given by an following equation:

$$\tau_i^j = \rho\tau_0 + (1-\rho)\tau_i^j . A_i^j + \rho\tau_i^j \quad (12)$$

In $\rho \in (0,1)$ is a parameter. As τ_0 is the minimum value of all pheromone values, the function of the local updating rule is to increase the value of τ_i^j to enhance diversity of the algorithm. To simulate the phenomenon of pheromone evaporation in real ant colony systems, the amount of pheromone associated with each A_i, which does not occur in the constructed rule must be decreased,. The reduction of pheromone of an unused term is performed by dividing the value of each τ_i^j by the summation of all τ_i^j.

C) Global Pheromone updating

Global pheromone updating is only applied at the end of each iteration. Global value is updated by K value which is n objects mapped to C_i^{Ki} Clusters at each iterations means $K_1, K_2, \ldots K_n$ are mapped i^{th} clusters.The global pheromone value is updated by

$$\tau_i^{K_i} = \rho\tau_i^{K_i} + (1-\rho)\tau_i^{K_i} + \rho K_i \qquad (13)$$

In this equation $\rho \in (0,1)$ is same parameter used in local pheromone updating. The global pheromone updating used to increase the pheromone values associated with the best-so-far solution so that these mappings will be more attractive in future iterations.

D) Cluster Construction

N ants set out to build solution to C clusters, here matching value of j^{th} object is constructed to ith cluster is defined by C_i^j. The selection rule of C_i^j is defined by

$$C_i^j = \delta_i^j \tau_i^j \beta^{\eta_i^j} \qquad (14)$$

Here, $\beta \geq 1$ is a parameter to determine the relative influence of pheromone and heuristic information. Heuristic values of each state mentioned above that satisfy $\eta_i^j \epsilon (0,1)$ so the values of $\beta^{\eta_i^j}$ satisfy $\beta^{\eta_i^j} \epsilon (0,1)$. In each iteration, every ant iterates this equation for N times so that N objects are constructed to N corresponding clusters and a complete solution is consequently built. In some case, if the quality of a partial solution built by an ant is already worse than the best-so-far ant, this partial solution will be deserted.

Experimental Result Analysis

The experimental results comparing Priority Based Pheromone Algorithm(PBPA) with several typical stochastic algorithms, including the normal ACO algorithm, the Genetic Algorithm , the basic k-means algorithm are provided for two artificial datasets (data 1, data 2) and one real-life datasets (Iris) respectively. In Artificial data set 1is a non overlapping two dimensional contains 1000 of data sets.Similarly Artificial data set2 contains 10000 of data sets. Real life data set iris which is perhaps the bestknown database to be found in the pattern recognition literature is tested by algorithm two times first time taken by 100 data sets and second time taken by 200 data sets. Here Minimum execution time is taken as Best Fitness and the results are compared by fitness and quantization errors. Both real and artificial data sets are run with 10,000, 20,000 and 50,000 number of iteration.Following are some sample experimental results of artificial data sets.

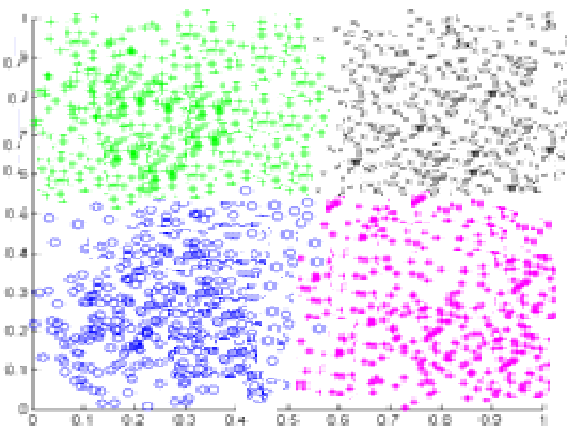


Figure 2. Initial Data

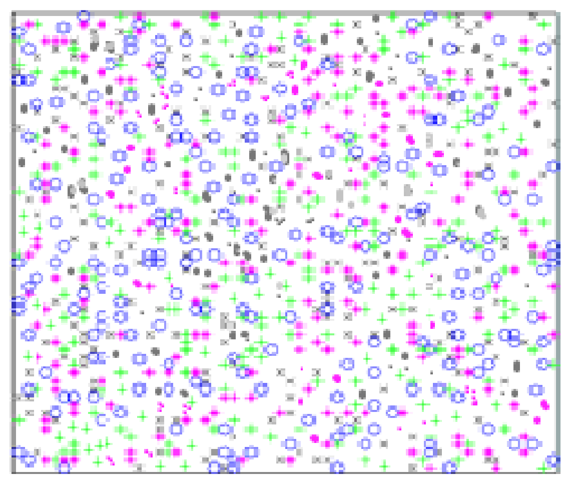


Figure 3. During Iteration

 ISSN: 2277-9655

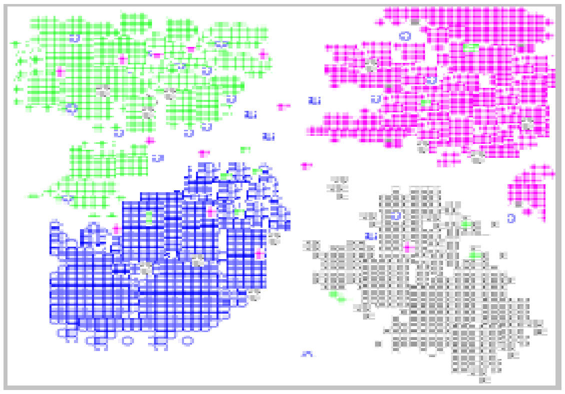
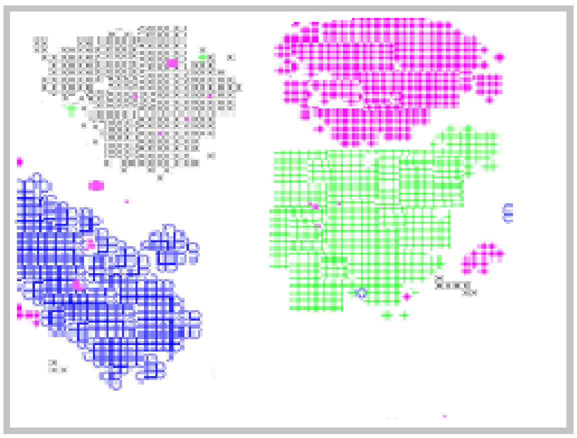


Figure 4. Result for 10000 iteration



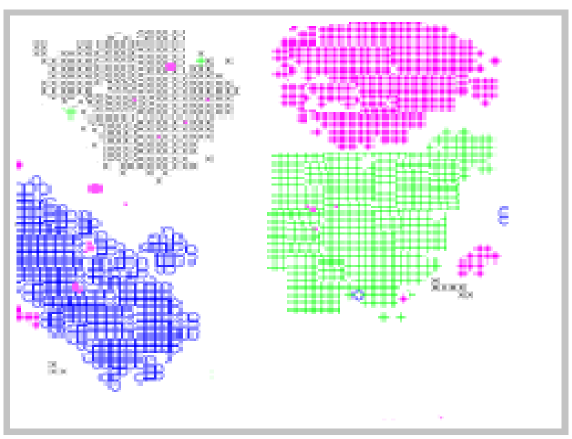


Figure 5. Result for 20000 iteration

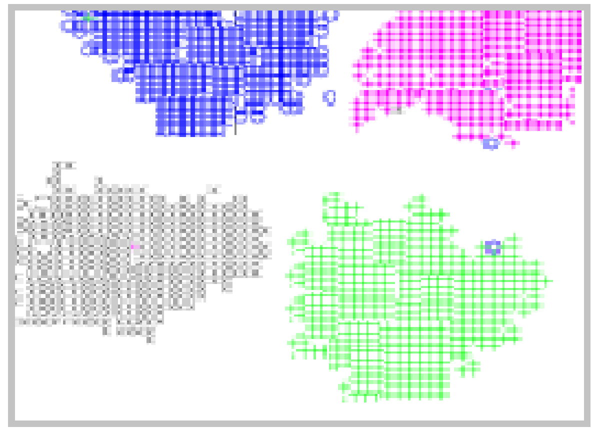


Figure 6: Result for 50000 iteration.

Table1: Experimental result for Artificial data sets with 1000 of data

Cluster Algorithms	Number of Iterations	K-Means	GA	ACO	PBPA
Best Fitness	10000	1720.1903	1396.2356	1210.3189	1077.8965
QE		6.1256	7.0231	5.7640	4.8960
Best Fitness	20000	2980.2713	3267.8920	2876.8989	2826.7532
QE		5.4914	5.2743	4.8796	3.0519
Best Fitness	50000	10028.9125	8828.3698	8027.8958	5973.0120
QE		3.8119	1.001	2.1911	0.0170

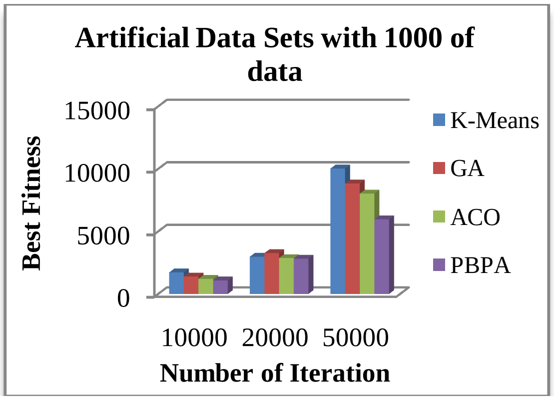


Figure 7. Performance analysis for artificial data sets

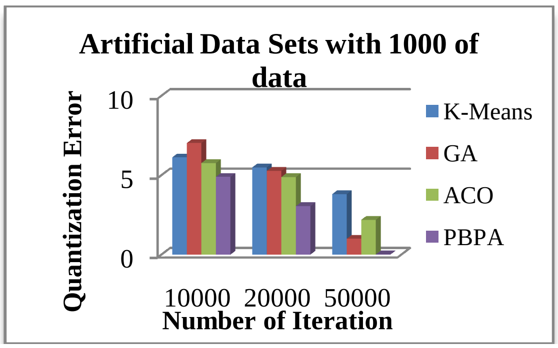


Figure 8. Performance analysis for artificial data with 1000 of data for Best Fitness sets with 1000 of data for QE

Table 2: Experimental result for Artificial data sets with 10000 of data

Cluster Algorithms	Number of Iterations	K-Means	GA	ACO	PBPA
Best Fitness	10000	16257.3841	15416.4201	15216.1001	16230.001
QE		226.68	98.29	83.13	56.12
Best Fitness	20000	32172.1670	22217.89	20176.33	12517.1014
QE		168.78	85.17	63.89	70.17
Best Fitness	50000	60100.2001	43217.8919	38900.1890	20267.8928
QE		88.21	33.12	49.21	17.89

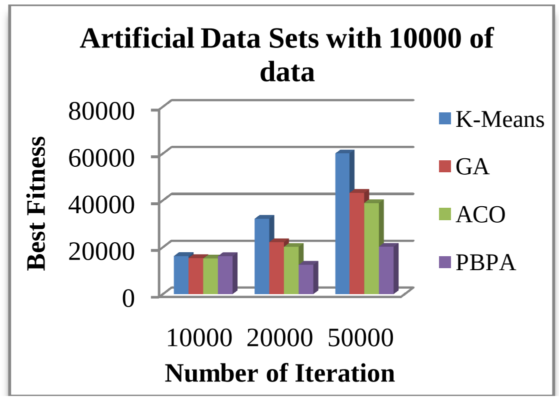


Figure 9. Performance analysis for artificial data sets

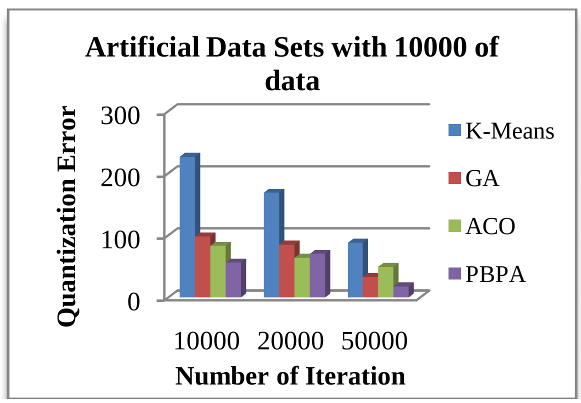


Figure 10. Performance analysis for artificial data with 10000 of data for Best Fit ness sets with 10000 of data for QE

Table 3: Experimental result for Real data sets with 100 of Imagedata

Cluster Algorithms	Number of Iterations	K-Means	GA	ACO	PBPA
Best Fitness	10000	493.1256	321.5698	456.0230	201.8564
QE		3.2569	1.0458	1.9635	0.1589

 ISSN: 2277-9655

Best Fitness	20000	875.36 89	654.2 867	561.0 258	597.3 691
QE		2.0045	0.256 9	0.125 4	0.569 8
Best Fitness	50000	1025.8 653	542.3 69	523.1 2	359.1 256
QE		1.5632	0.002 5	0.002 5	0.000 1

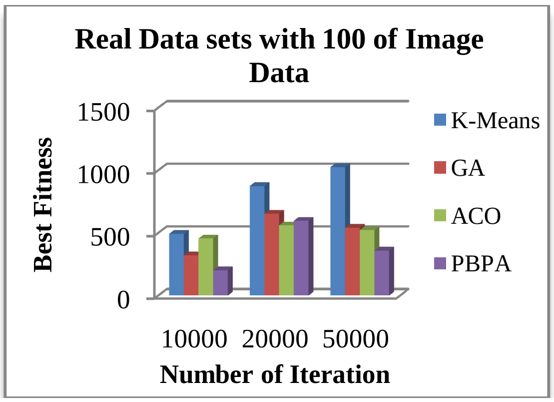


Figure 11. Performance analysis for real data sets

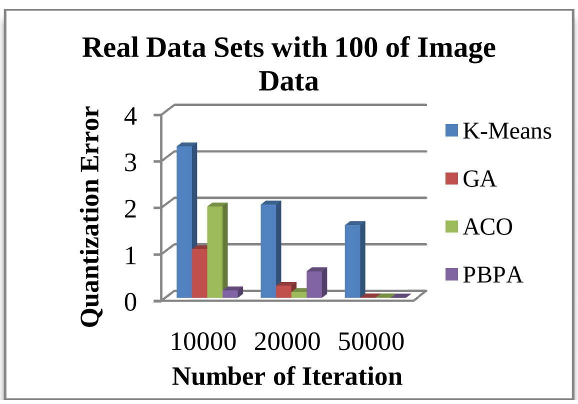


Figure 12. Performance analysis for real data with 100 of Image data for Best Fitness sets with 100 of Imagedata for QE

Conclusion

In this paper we proposed a new algorithm to Ant Colony System called Priority based pheromone algorithm. Key features of this algorithm is to find path by combination of three major methods priority value, Pheromone value and heuristic information. In this algorithm maximum number of iteration is used to found better optimal cluster. In this paper we have explored the capability of Priority Based Pheromone Algorithm on some well data sets. Although Genetic Algorithm and normal Ant Colony Algorithm is established good but it has some demerits in large sets of data on both artificial data sets and real image data sets. Also, results illustrate our proposed algorithm is best as with compared algorithm. We have idea to continue this algorithm in more realistic data sets like medical and in logistical domain.

References

[1] E. Bonabeau, M. Dorigo and G. Theraulaz, “Swarm Intelligence: from natural to artificial systems”, Oxford University Press, Inc., New York, NY, 1999

[2] Abraham, He Guo and Hongbo Liu, “Swarm Intelligence:Foundations, Perspectives and Applications”, Swarm Intelligence in Data Mining, A. Abraham, C. Crosan, V. Ramos (Eds.), Studies in Computational Intelligence (series), Springer, Germany, 2006.

[3] Dai, W., Xu, D.: “Customer clustering analysis: A new algorithm based on swarm intelligence”. In :2010 4th International Conference on New Trends in Information Science and Service Science (NISS), Gyeongju, pp.599-603 (11-13 May 2010).

[4] Jiang, H., Gong, Y-Y.: “An improved ant colony clustering algorithm”. In : 2010 3rd International Conference on Biomedical Engineering and Informatics (BMEI), Yantai, vol. 6, pp.2368-2372(16-18 Oct. 2010).

[5] Marco Dorigo and Thomas Stutzle, “Ant Colony Optimization”, Prentice-Hall of India Private Ltd., New Delhi, 2006.

[6] G. DI Caro and M. Dorigo, “Extending AntNet for Best-effort Quality-of-Services Routing”, Ant Workshop on Ant Colony Optimization, http://iridia. ulb.ac.be/ants 98/ants98.html, 1998, pp. 15-16.

[7] Marco Dorigo and Thomas Stutzle, “The Ant Colony Optimizaion Metaheuristic: Algorithms, Applications, and Advances”, In: F. Glover and G. Kochenberger (Eds.), Handbook of Metaheuristics, Kluwer Academic Publishers.

[8] Manfrin,M., Birattari, M., Stützle,T., Dorigo, M.: “Parallel and colony optimization for the traveling salesman problem. In : Ant Colony Optimization and Swarm Intelligence”5th International Workshop, ANTS 2006, Berlin, Germany, vol. 4150, volume of Lecture Notes in

Computer Science., pp.1161-1172 (2006).
[9] Manfrin, M., Birattari, M., Stützle, T., Dorigo, M.: "Parallel Multicolony ACO Algorithm with Exchange of Solutions". In : IRIDA, Brussels, Belgium.
[10] Parpinelli, R.S., Lopes, H.S., Freitas, A.A.: "An ant colony based system for data mining: Applications to medical data". In : Genertic and Evolutionary Computing. Conference., pp.791-797(2001).
[11] Parpinelli, R.S., Lopes, H.S., Freitas, A.A.: "Data mining with an ant colony optimization algorithm". In : IEEE, Transactions on Evolutionary Computation, pp.321-332 (2002)
[12] JI, J., Zhang, N., Liu, C., Zhong, N.: "An Ant Colony Optimization Algorithm for Learning Classification Rules". In : 2006. WI 2006. IEEE/WIC/ACM International Conference on Web Intelligence, Hong Kong, pp.1034-1037 (18-22 Dec. 2006)
[13] Roselin, R., Thangavel, K.: "Classification ensemble for mammograms using Ant-Miner". In : 2010 International Conference on Computing Communication and Networking Technologies (ICCCNT), Karur, pp.1-6 (29-31 July 2010)
[14] Moayed, M.J.: "Ant colony algorithm for web page classification". In : 2008. ITSim 2008.International Symposium on Information Technology, Kuala Lumpur, vol. 3, pp.1-8 (26-28 Aug.2008)
[15] Michelakos, I., Papageorgiou, E., Vasilakopoulos, M.: "A Hybrid Classification Algorithm Evaluated on Medical Data".In : 2010 19th IEEE International Workshop on Enabling Technologies: Infrastructures for Collaborative Enterprises (WETICE), Larissa, pp.98-103 (28-30 June 2010).