A Proposal to Modulate ACS (Case study: Clustering Ionosphere database using FCM)

مقترح لتنغيم خوارزمية مستعمرة النمل

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Abstract

This work trend to strength ACS, which is used as a solution for optimization problems, to make ACS more efficient and strongest to face the most important problems and faults in it is infrastructure, these problems are local optimum and stagnation. The enhancement is done by building proposed algorithm is called Modulated ACS, which is a trend to optimal solution by efficient treatment for local optimum and stagnation. PSO has been exploited as a solution to solve the both problems; that by modulates ACS by PSO parameters to converge the global and local updates. Several experiments are conducted to prove the robustness and strength of proposed Modulated ACS algorithm. The experimental works was done by applying traditional ACS and modulated ACS as an attribute reduction for Ionosphere database which include 351 instances, with Fuzzy C-Mean (FCM) clustering algorithm. The results show that; the modulated ACS introduces optimal time for finding the solutions than the traditional ACS. The modulated ACS reduces 50% of overall time spent by traditional ACS and the precision of clustering with traditional ACS was have 51 outlier instances between two clusters, where the precision of clustering with modulated ACS was have just 13 outlier instances between two clusters.

Keywords: congestion, stagnation, ACS, PSO, FCM.

الخلاصة

هذا العمل يتوجه لتقوية خوارزمية مستعمرة النمل والتي تستخدم كحل لمشاكل الامثلية، وذلك لجعل ACS اكثر كفاءة وقوة لمواجهه اهم المشاكل والاخطاء التي تعتبر جزء من بنيتها التحتية. هذه المشاكل هي المثلى المحلية والركود. التحسين تم من خلال بناء خوارزمية مقترحة تسمى مستعمرة النمل المنغمة، والتي تقود الى الحل الامثل بالتعامل الاكفاء مع المثلى المحلية والركود. خوارزمية امثلية الجسيمات المتجمعه تم استثمارها كحل لكلا المشكلتين من خلال تنغيم مستعمرة النمل بمعاملات الجسيمات المتجمعه لتقريب التحديث المحلي والعام لمستعمرة النمل. العديد من التجارب تم ترشيحها لاثبات قوة المقترح لتنغيم مستعمرة النمل. التجارب كانت تتضمن تطبيق مقلص الخصائص بواسطة خوارزمية المستعمرة التقليدية والمستعمرة المنغمة على قاعدة بيانات الغلاف الايوني المتضمنة 351 قيد (حالة) مع خوارزمية العنقدة FCM. النتائج اظهرت ان مستعمرة النمل المنغمة قلصت وقت الوصول للحل الامثل الى مايقارب 50% من الوقت المستغوق في المستعمرة التقليدية وكذلك دقة العنقدة في المستعمرة التقليدية كانت قليلة بسب وجود 51 حالة شاذة بين الصنفين بينما المستعمرة المقترحة ترتفع فيها دقة العنقدة حيث ان الحالات الشاذة هي 13 فقط.

1. Introduction

In ACS the rule of transition probability provide a method to stable exploration of next edges and exploitation of a known and heaped knowledge about the problem[1],

$$S=\begin{cases} \arg\max_{u\epsilon J_{k(r)}} \left\{[\tau(i,j)].[\eta(i,j)]^{\beta}\right\} & if\ q \le q_0 \ \ (exploitation) \\ \\ S & otherwise \qquad (biased\ exploration) \end{cases} \quad (1)$$

where τ(i, j) is the pheromone trail of link "edge" (i, j), the heuristic appeal η(i, j) = 1/d_{ij} is the inverse of the length from node i to node j (η(i,j)), s_k (i) is the set of nodes that still to be listed by ant k positioned on node i. Also, β is a parameter which determines the relative intrinsic of pheromone versus distance (β >0), q_0 is a random number uniformly distributed in [0, 1], and q_0 is a parameter ($0 \le q_0 \le 1$) which determines the relative importance of exploitation versus exploration. In addition, S is a random variable which affords the probability with where the ant k in node i selected to transit to node j that is chosen by probability distribution. The rules of transition probability obtain from Eq. (1) and (2) is called pseudo-random-proportional rule [2, 3].

$$\rho^k(i,j) = \frac{[\tau(i,j)]^{\alpha}[\eta(i,j)]^{\beta}}{\sum_{i\epsilon n^k}[\tau(i,j)]^{\alpha}[\eta(i,j)]^{\beta}} \quad (2)$$

The rule of global updating is done just to links which stun to the optimal ant tour, and

$$\tau(i,j) \leftarrow (1-a)\cdot\tau(i,j) + a\cdot\Delta\tau(i,j) \quad (3)$$

$$\text{Where} \begin{cases} (L_{gb})^{-1} & if\ (i,j) \in global-best-tour \\ \\ 0 & otherwise \end{cases}$$

Where 0<α<1 is the degeneracy parameter of the pheromone, and L_{gb} is the length of the best global tour from the start of the trial. The updating of global is aimed to supply a big amount of pheromone to the tours which are shorter. Eq. (3) determine that only those links are stun to the best tour in global will receive reinforcement. While ants build a solution a rule of pheromone updating locally is done. While constructing a solution, ants visit links and their pheromone level are changed by applying the rule of the local updating as in Eq. (4).

$$\tau(i,j) \leftarrow (1-\rho)\cdot\tau(i,j) + \rho\cdot\Delta\tau(i,j) \quad (4)$$

Here, 0< ρ<1 is the degeneracy parameter of the local pheromone. The impact of local-updating is to make the eligibility of links change in dynamic. Every time an ant uses an edge, it becomes a little less eligible because it perishes some of its pheromone less desirable will make for next ants and to allow for the discover of the new and may better tours in the near of the last optimal tour [3, 4].

Particle Swarm Optimization (PSO) is initialized with a set of random solutions and then discover for optima by generations updating. So with every iteration, each particle will be updated by two values called "best". The rule of particle update presented in Eq. (5) and Eq. (6).

$$p = p + v \quad (5)$$

$$v = v + c_1 * rand * (pBest - p) + c_2 * rand * (gBest - p) \quad (6)$$

where *p*: particle's position, *v*: path direction, c_1: weight of local information , c_2: weight of global information, *pBest*: the particle's best position, *gBest*: the swarm's best position, *rand*: random variable [5, 6, 7].

Hard c-means algorithm is used to cluster 'm' records into 'c' clusters. Each cluster has its cluster center. The records belong to the cluster which has the least distance from it. The clustering is crisp, which means that each record is clustered into one and only one cluster. FCM is a variation of the hard c-means clustering algorithm. Every record here has a membership value associated with each of the clusters which is related inversely to the distance of that record from the center of the cluster [8].

2. Problem Statement and Contribution

ACS is still one of the most important algorithms used in optimization problems; from the survey through many researches of ACS and it is application there are some of problems still unsolved with ACS such as stagnation, tables freezing and local optimum. The contribution is trend to solve these problems by injecting the transition rules and both local and global updating rules with PSO parameters to converge the local and global update. By that ACS will be stimulated consciously through all the iterations and then the stagnation and local optimum will fade. Clustering still suffer from overlapping, the proposal trend to use FCM to reduce the outliers as much as possible and to be justify in evaluating the two feature selection methods.

3. Mathematical Model of Proposed Modulated ACS

The proposed enhancement for ACS concentrates on two critical dimensions in network routing algorithms generally. These two dimensions are: local optimum and stagnation, the proposal aim to solve these two problems by inject PSO parameters with ACS; that by use learned PSO parameters in both transition rules and update rules of ACS.

The proposed Modulated ACS will learn the parameters of the PSO algorithm; which can be used in the transition probability and rules of pheromone update. Then the results of proposed algorithm will adapter the ACS to be strong to detect the local optimum since ACS will be stimulated by PSO to cancel the freezing of routing tables, stagnation, and prevent the local optimum. So an effectiveness algorithm in a stagnated environment must be able to continuously adapt the solutions in the freezing environment.

Where the Transition Probability is the effective factor contributes in ACS and by it the ant will choose the next nodes. And the pheromone update which is initiated randomly at the beginning of ACS and changed continuously present the intrinsic role of ACS cause by it will identify the direction of search in overall network. For that will introduce a proposed movement transmission by hybrid the traditional rule with PSO to strength the searching of ants to discover the optimal path fast. The proposal will introduce a proposed hybrid proposed mathematical model Eq. (7) for arriving to characterize of exploration and exploitation.

$$\rho^k(i,j) = \frac{[\tau(i,j)+\boldsymbol{Z1}]^\alpha[[\eta(i,j)]+\boldsymbol{Z2}]^\beta}{\sum i\epsilon n^k[\tau(i,j)+\boldsymbol{Z1}]^\alpha[[\eta(i,j)]+\boldsymbol{Z2}]^\beta} \qquad (7)$$

Where

$$z1= c1*r1 \qquad (8)$$

and

$$z2=c2*r2 \qquad (9)$$

So, the proposed mathematical model will inject a PSO parameters z1 and z2 to optimize the transition rules of ACS. For local pheromone updating will exploit c1 parameter of PSO to find optimal local solution. The proposed local pheromone updating equation is shown in Eq. (10).

$$\tau(i,j) \leftarrow (1-\rho)\cdot\tau(i,j).\boldsymbol{c1} + \rho\cdot\Delta\tau(i,j) \qquad (10)$$

Eq. (10) present local update which is enhanced by adding the parameter c1, for global pheromone updating will exploit c2 parameter of PSO to find optimal global solution. The proposed global pheromone updating equation is shown in Eq. (11).

$$\tau(i,j) \leftarrow (1-a)\cdot\tau(i,j).\boldsymbol{c2} + a\cdot\Delta\tau(i,j) \qquad (11)$$

Eq. (11) present global update which is enhanced by adding the parameter c2, $\Delta\tau(i,j)$ will obtained by Eq. (12)

$$\Delta\tau(i,j) = q/\left(L_{gb}\right) \qquad (12)$$

4. The Proposed Algorithm of Modulated ACS

The proposal will explained in details by the following algorithm (1). Before describe the algorithm will describe it is outlines in the following statements; Modulated ACS is a traditional ACS injected with PSO, where each ant will travel through search space will do the traditional transition rules then select the both best of the ant (which play in this step the role of the particle) so will find pbest and gbest. Then update the pheromone according these values and then update the global best position. Finally continue to complete the traditional ACS stop conditions.

Algorithm (1) Modulated ACS
Input: Initial parameters for ACS and PSO **Output**: Best solution according termination conditions of ACS and PSO
Process: 1. Begin a travelling through search space by distributes pairs of ant and the support-particle randomly on the search space. 2. While stopping conditions not reached (no more best solutions with ants and the maximum number of ACS iteration is at least 50) • For each support-particle calculate pbest and gbest, 1. For i=1 to max iteration (maximum number of PSO iteration is at least 30) 2. For each support-particle (sp in search space) do 3. fsp = f(sp); 4. If fsp is better than f(pBest) 5. pBest = sp; 6. end 7. end gBest = best sp in search space; 8. For each support particle sp in search space do 9. Calculate Eq. (5) and Eq. (6). 10. End • For each ant calculate transition probability, using Eq. (7), which is proposed ACS injected with PSO. • Update pheromone in local and global, using Eq. (10) and Eq. (11), which are proposed ACS injected with PSO. 3. End while 4. Consider the best solution as a final output of the proposed Modulated ACS. **End Process**

5. The Proposed Algorithm of Modulated ACS

For clustering will use FCM clustering algorithm; which is minimize the overlapping in clustering. Algorithm (2) will present the customized FCM for clustering the dataset two times; first for features selected by traditional ACS and the second for features selected by modulated ACS.

Algorithm (2) Customized FCM

Input: Dataset to be clustered

Output: Number of clusters (according to the dataset of the problem) each cluster has it is elements with high degree of similarity.

Process:

1. Construct the initial matrix of fuzzy partition, the matrix M=[Mij], $M^{(0)}$

$$\text{Mij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{\|xi-cj\|}{\|xi-ck\|}\right)^{\frac{2}{u-1}}} \quad \ldots\ldots\ldots\ldots\ldots\ldots \text{(13)}$$

Where

- u is a real number should be large than 1, in this proposal taken as u=2.
- m*ij is* the degree of membership of xi in j*th* cluster
- x*i* is i*th* element of the data, in the proposal the element is each feature in the dataset.
- c*i* is the i*th* element of the cluster center.

2. Calculate the vectors of centers $C^{(k)}$ = [cj] with $M^{(k)}$ using the following equation,

$$\text{Cj} = \frac{\sum_{i=1}^{n} uij^{m} * xi}{\sum_{i=1}^{n} uij^{m}} \quad \ldots\ldots\ldots\ldots\ldots \text{(14)}$$

3. Update $M^{(k)}$, $M^{(k+1)}$using the eEq. (13).

4. MF = $\left\|M^{(k+1)} - M^{(k)}\right\|$, If $MF < E$ then End, else go to step 2.

Where

- MF is higher change in the values of fuzzy partition matrix, this value calculated using the objective function of minimization is,

$$\text{Jm} = \sum_{i=1}^{n}\sum_{j=1}^{c} uij^{m} \ \|xi - ci\|^{2} \quad \ldots\ldots\ldots\ldots\ldots\ldots \text{(15).}$$

- E is conditions of termination with value ranged in [0, 1].

End Process

6. Implementation and Experimental Works

To prove the proposed modulated ACS will present a case study compare between the performance of both traditional ACS and Modulated ACS. The case study is the reducing attribute problem; is an optimization problem. The dataset is selected to apply the feature selection on it is Ionosphere database which has 351 of instances and 34 continuous attributes and the aim is to cluster this database into two clusters, so the 35^{th}attribute is either "good" or "bad" represented as a binary (0 or 1) will be filled according FCM clustering algorithm one time using traditional ACS and other time using Modulated ACS.

Now to implement the traditional ACS and Modulated ACS there are many parameters must be initiated, these parameters are:

- For Traditional ACS and Modulated ACS

1. α values from 0.5 to 2.
2. β values from 2 to 5.
3. ρ value is 0.5.
4. probability q_o for exploitation
5. probability (1- q_o) for exploration

6. C1 is the importance of personal best value,
7. C2 is the importance of neighborhood best value,
8. Usually C1 + C2 = 4 (empirically chosen value),
9. If velocity is too low → algorithm too slow,
10. If velocity is too high → algorithm too unstable.

By using traditional ACS the attributes are ranked as in the following;

```
Selected attributes: 1,28,18,5,7,20,24,33,6,27,26,32,29,3,14,34,21,8,31,22,16,4,9,13,23,25,12,15,10,30,11,17,19,2 : 34
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Where using modulated ACS the attributes are ranked as in the following;

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Selected attributes: 5,6,33,29,3,21,34,8,13,7,31,22,23,27,4,16,15,17,12,25,9,11,28,19,14,10,18,24,20,1,32,26,30,2 : 34
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By taking the 20^{th} first high ranked of both traditional and modulated ACS then apply clustering for each case the following results are obtained, see table (1).

Table (1): Results of time and precision of both Traditional ACS and Modulated ACS according FCM clustering

Methods/Evaluations	Parameters	Total Time	Clustering FCM (two clusters)
Traditional ACS	$\alpha = 1$ $\beta = 2$ $\rho = 0.5$	00:00:45	With high 20^{th} attribute: outliers= 51 instance from total 351,
Modulated ACS	$\alpha = 1$ $\beta = 2$ $\rho = 0.5$ C1 = 2 C2 = 2	00:00:22	With high 20^{th} attribute: outliers= 13 instance from total 351,

6. Conclusions

The research reached to the following conclusions.

1. ACS and PSO, each of them search for maximize or minimize, it has no stimulation so it always suffer from stagnation and local optimum.
2. By hybrid ACS with PSO to construct the modulated ACS, PSO stimulate the ACS solutions through the learning parameters of PSO and enhance the convergence of local and global updates.
3. By injecting PSO with ACS the time of finding the optimal solution is decreased to half due to the learning parameters of PSO which are strength the rules transition probability.
4. As a feature reduction problem is the base bone of clustering and classification application since it reduces the number of features aiming to remove irrelevant features. Modulated ACS give best 20^{th} features than the 20^{th} features given by traditional ACS. That proofed by the time reduced and the decreased outliers instances between two clusters.
5. FCM is a high quality clustering method since it never clusters an element error; instead it considers it outlier. So the results of FCM with modulated ACS have no bias or Prejudice.

References

1. Vijayalaxmi, Adiga C. S., Joshi H. G. and Harish S.V.: "Computational intelligence approaches and Evolutionary algorithms: A Study for Financial Derivatives", International Journal of Advances in Engineering Science and Technology, volume 1, number 2, 2013.
2. Yoshikawa M., Otani K., "Ant Colony Optimization Routing Algorithm with Tabu Search", proceedings of the International Multiconference of Engineers and Computer Scientists Vol.3, 2010.
3. NK C. and Viswanatha K. V.: "Routing in Dynamic Network using Ants and Genetic Algorithm", R V College of Engineering, Bangalore, India, published by Elsevier , 2013.
4. Jaiswal U. and Aggarwal S.: "Ant Colony Optimization", International Journal of Scientific & Engineering Research Volume 2, Issue 7, July-2011.
5. Garg A., Gill P., Rathi P., Amardeep and Garg K.: "An Insight into Swarm Intelligence", International Journal of Recent Trends in Engineering, Vol 2, No. 8, November 2009.
6. Venter, G. and Sobieski, J., "Particle Swarm Optimization," AIAA 2002-1235, 43rd AIAA/ASME/ASCE/ AHS/ASC Structures, Structural Dynamics, and Materials Conference, Denver, CO., April 2002.
7. Kennedy J., Eberhart R. C., "Particle Swarm Optimization", In Proceedings of the IEEE International Conference on Neural Networks, pp. 1942-1948, 1995.
8. Nogueira, T.M. ; " On The Use of Fuzzy Rules to Text Document Classification "; 2010 10^{th}, International Conference on Hybrid Intelligent Systems (HIS),; 23-25 Aug 2010 Atlanta, US.