An Analysis of Ant Colony Clustering Methods: Models, Algorithms and Applications

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Abstract

In recent years the ant colony clustering methods have emerged as a new kind of data mining schemes. The research of ant colony clustering methods is also an important direction for swarm intelligence. Today these methods have been deeply investigated and most of them show good performance. This paper will give an analysis of ant colony clustering methods from the perspective of models, algorithms and applications. First we introduce two important ant colony models: “foraging model” and “piling model”, by which most ant colony clustering methods are inspired. Based on these two models, we present a survey on main ant colony clustering algorithms. Meanwhile, a classified summary of applications is given. We finally discuss our opinions on future research about ant colony clustering methods.

Keywords: Ant Colony Clustering, Clustering Analysis, Ant Colony Optimization

1. Introduction

In the field of data mining and knowledge discovery, clustering analysis is a kind of unsupervised learning method, which aims at grouping a set of data objects into clusters, based on one or more features of the data. Data objects are similar to one another within the same cluster and are dissimilar to the objects in other clusters. Generally speaking, major clustering techniques are classified as follows: partitioning methods, hierarchical methods, density-based methods, grid-based methods, and model-based methods. In addition, some clustering techniques combine the ideas of several clustering methods. Nevertheless, every clustering method has its own limitation. For instance, K-means algorithm, a widely used partitioning method, depends too much on the initial objects which may result in local optimum, and the number of clusters needs to be specified in advance. In recent years, swarm intelligence has been introduced into the clustering analysis field to solve some existing problems.

Swarm intelligence realizes the artificial intelligence by modeling the group behavior of social animals, such as birds, fishes, bees and ants. In this kind of groups, a single individual's intelligence is not high, but relying on the ability of groups, the swarm intelligence exceeds the total intelligence of individuals greatly. It has been applied in various combinatorial optimization problems, including the traveling salesman problem (TSP), quadratic assignment problem, graph coloring, job-shop scheduling, sequential ordering, and vehicle routing [1].

The advantages of swarm intelligence can be described as follows [2][19]:
1. There is no centralized control system, so the paralysis of one or some individuals cannot affect the ultimate solution of the whole system.
2. In the system, individuals work and distribute in an independent and cooperative way, suitable for a network environment.
3. The individuals do not communicate with each other in a direct way, but an indirect way. Hence it would not bring too much communication cost if the group scale increases. It is beneficial to the system extensibility.
4. The realization of the whole system is convenient due to the simple function and the short execution time of each individual.

Ant colonies, as one important research direction of swarm intelligence studies, has been fully investigated and applied in many fields during these years [20]. Ant colonies have the characteristics of self-adaptation, self-organization, flexibility, robustness, parallel computing, no need of prior information, etc. Ant colony clustering algorithms is also helpful to effective in solving clustering problems. There are two kinds of ant colony methods for clustering: One is based on ant colony optimization (ACO) algorithm which is inspired by behaviors of ant colonies finding the shortest path between their nest and a food source; the other one is inspired by the behavior of ant colonies in clustering their corpses and sorting their larvae. Based on the two ant colony models, this paper will survey the researches of ant colony clustering algorithms as well as some applications.

The remaining of this paper is organized as follows: In section 2, we will give a brief review of the clustering analysis problems. Section 3 describes the two kinds of ant colony clustering models. Section 4 presents an overview of existing researches in the ant colony clustering field. In section 5, we briefly introduce the applications of ant colony clustering algorithms. Finally, a summary of this paper is offered in section 6.

2. Clustering analysis problems

<table>
<thead>
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<th>Detectable cluster shape</th>
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<td>PAM</td>
<td>Convex</td>
<td>Weak</td>
<td>Weak</td>
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<td>CLARA</td>
<td>Convex</td>
<td>Strong</td>
<td>Weak</td>
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<tr>
<td>Hierarchical methods</td>
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<td>BIRCH</td>
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<td>CURE</td>
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<td>Moderate</td>
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<td>ROCK</td>
<td>Arbitrary</td>
<td>Moderate</td>
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<td>Linkage</td>
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<td>Chameleon</td>
<td>Arbitrary</td>
<td>Moderate</td>
<td>Strong</td>
<td>Linkage</td>
<td>Agglomerative or Diverse</td>
<td></td>
</tr>
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<td>Density-based methods</td>
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<td>DBSCAN</td>
<td>Arbitrary</td>
<td>Strong</td>
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<td>OPTICS</td>
<td>Arbitrary</td>
<td>Strong</td>
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<td>DENSITY</td>
<td>Arbitrary</td>
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<td>Very strong</td>
<td>Density</td>
<td>Optimization</td>
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<td>Grid-based methods</td>
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<td>STING</td>
<td>Arbitrary</td>
<td>Very strong</td>
<td>Weak</td>
<td>Density</td>
<td>Agglomerative</td>
<td></td>
</tr>
<tr>
<td>Wavecluster</td>
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<td>Very strong</td>
<td>Strong</td>
<td>Density</td>
<td>Search</td>
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<tr>
<td>CLIQUE</td>
<td>Convex</td>
<td>Moderate</td>
<td>Very strong</td>
<td>Density</td>
<td>Search</td>
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<tr>
<td>Swarm clustering methods</td>
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<tr>
<td>Ant colony clustering</td>
<td>Arbitrary</td>
<td>Strong</td>
<td>Strong</td>
<td>Density</td>
<td>Optimization</td>
<td></td>
</tr>
</tbody>
</table>
Clustering analysis is the division of the data set into clusters of similar objects. According to a certain pattern, the data set is grouped. Its mathematical description shows as follows:

Supposed the sample set is $E$, and the class $C$ is a nonempty subset of $E$,

$$C \subset E, C \neq \emptyset$$

(1)

Clustering is the collection of classes that satisfy the following two conditions,

$$(1) C_1 \cup C_2 \cup \ldots \cup C_k = E$$

$$(2) C_i \cap C_j = \emptyset, i \neq j$$

(2)

That is to say, each sample in sample set $E$ should belong to one and only one of the classes.

The four main classes of clustering algorithms are partitioning methods, hierarchical methods, density-based methods and grid-based methods. In this section, we just make a comparison of various clustering algorithms, including the methods mentioned above and the swarm clustering method. It is shown in Table 1.

Besides the items listed in Table 1, the colony clustering algorithm has the advantages of no need to specify complex parameters and prior information such as the number of clusters. Many following researches also enhance this kind of algorithms. The details about these contributions will be discussed later in this paper.

3. Two ant colony behavior models

In existing researches, the ant colony clustering algorithms involves two kinds of ant colony models. One is based on ACO algorithm which is inspired by the foraging behavior of real ant colonies. The other is inspired by piling the corpses and larval-sorting behaviors of real ant colonies.

Before we survey the previous contributions of the ant colony clustering algorithms, these two kinds of ant colony behavior models will be analyzed here for the sake of better understanding.

3.1. Foraging model

In nature, when ants leave their nest to search food, they will deposit pheromones on the path as the information to other ants passing by. According to the density of the pheromones, ants will be eventually guided to find the shortest way from the nest to the food source. The double-bridge experiment performed by Goss et al. could explain this problem. As shown in Figure 1, the number of ants on the longer and shorter paths is basically the same in the 4th minute of the experiment. 4 more minutes after that, almost all ants choose the shortest path between foraging source and their nest. Supposed that ants move at the same speed, the intensity of pheromone on shorter path is higher than the other path because a round move on shorter path costs less time.

![Figure 1. Double-bridge experiment](image)

Based on this foraging model, the first ACO algorithm was developed by Dorigo et al. [3]. At each construction step, the probability conversion function of an ant $k$ moving from location $i$ to location $j$ is computed as:
\[ p_{ij}^k(t) = \begin{cases} \frac{[\tau_{ij}(t)]^\alpha \cdot [\eta_{ij}(t)]^\beta}{\sum_{j \in \text{allowed}_k} [\tau_{ij}(t)]^\alpha \cdot [\eta_{ij}(t)]^\beta} & j \in \text{allowed}_k \\ 0 & \text{other} \end{cases} \] (3)

where \( \text{allowed}_k \) represents all the next location that ant \( k \) could reach; \( \alpha, \beta \) are two heuristic factors that weight the relative importance of the pheromone trail and the heuristic information; \( \eta_{ij}(t) \) is heuristic function, which is expressed as:

\[ \eta_{ij}(t) = \frac{1}{d_{ij}} \] (4)

where \( d_{ij} \) refers to the distance between location \( i \) and \( j \).

The pheromone information is to be updated after every construction step of the ants. It is defined that the pheromone information at time \( t+n \) can be defined as follows:

\[ \tau_{ij}(t+n) = (1-\rho) \cdot \tau_{ij}(t) + \Delta \tau_{ij}(t) \] (5)

\[ \Delta \tau_{ij}^k(t) = \sum_{j=1}^{m} \Delta \tau_{ij}^k(t) \] (6)

where \( \rho \) is the evaporate coefficient of the pheromone, and \( 1-\rho \) represents deposited factor; \( \Delta \tau_{ij}^k(t) \) represents the amount of information left on the path \((i, j)\) by the \( k \)th ant.

### 3.2. Piling model

In this paper, we call the other ant colony model “piling model”. In Figure 2, the experiment performed by Deneubourg [4] shows a real ant colony performing the task of piling 1500 ant corpses during 26 hours. This experiment proved that some species of ant colony (Pheidole Pallidula and Lasius Niger) have the ability to pile the corpses to form a “cemetery”. Besides, other species of ant colony (Leptothorax unifasciatus) are observed to be able to sort and cluster the larvae to a structure with smaller larvae in center and larger larvae on the edge.

![Figure 2](image)

**Figure 2.** Randomly distributed ant corpses are clustered in cemeteries in 36 hours [1]

Although such behavior has not fully explained in biology field, an effective clustering model is extracted and proposed first by Deneubourg et al. [4]. This model is based on the rules of picking up
and dropping down of the single ant. The data objects are randomly mapped into a 2-dimension grid space. Each single ant moves randomly on this grid to pick up and drop down the data objects. If one object has a lower similarity with objects in its neighborhood, it would have a higher probability to be picked up by ants; and if an object being carried by an ant has a higher similarity with objects in its neighborhood, it would have a higher probability to be dropped down.

The probabilities of picking up and dropping down an object are given by:

\[
P_p = \left( \frac{k_1}{k_1 + f} \right)^2 
\]

\[
P_d = \left( \frac{k_2 + f}{k_2 + f} \right)^2 
\]

Where \( f \) is the perceived fraction of objects in the ant’s neighborhood, reflecting the similarity with its neighborhood; \( k_1 \) is a threshold constant; \( k_2 \) is another threshold constant. Generally, the probabilities of picking up and dropping down are opposite.

3.3. Comparison of the two models

Both the foraging model and the piling model have their own characteristics and application scene, although they are all suitable for promoting clustering research. The comparison between these two models is shown in Table 2.

<table>
<thead>
<tr>
<th>Element</th>
<th>Real ant colony</th>
<th>Foraging model</th>
<th>Piling model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Activity of a single ant</td>
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<td>Picking up and dropping down the object of a single ant</td>
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<tr>
<td>Behavior pattern</td>
<td>Affected by each other</td>
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<td>Affected by the similarity in the neighborhood on 2D grid</td>
</tr>
<tr>
<td>Problem space</td>
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<td>Depending on the problem being optimized (e.g. clustering problem)</td>
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<tr>
<td>Function</td>
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<td>Self-organized optimization</td>
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</tr>
<tr>
<td>System evolution</td>
<td>Survival and reproduction</td>
<td>Finding the optimal solution</td>
<td>Convergence</td>
</tr>
</tbody>
</table>

4. Main algorithms survey

4.1. Clustering algorithms based on foraging model

Based on foraging behavior of ant colony, Dorigo et al. [3] proposed ACO as a meta-heuristic approach, to solve several discrete optimization problems. ACO has been applied in many fields, such as traveling salesman problem (TSP), scheduling, vehicle routing, quadratic assignment problem, routing optimization in telecommunication networks and graph coloring.

Tsai et al. [5] proposed a novel clustering method called ant colony optimization with different favor algorithm (ACODF). The ACODF algorithm has three important desirable strategies: 1) using ants with different favor to solve the clustering problem, 2) adopting simulated annealing concept for ants to decreasingly visit the amount of cities to get local optimal solutions, 3) utilizing tournament selection strategy to choose a path. This algorithm performs better than the fast self-organizing maps (FSOM) + K-means and genetic k-means algorithm (GKA).

Shelokar et al. [6] presented an ant colony optimization methodology for optimally clustering. Distributed ant agents are employed to finish the clustering task. The performance of this algorithm is compared with other popular heuristic methods, including genetic algorithm, simulated annealing and...
tabu search. The computational simulations reveal very encouraging results in terms of the quality and the efficiency.

Chu et al. [7] extends ant colony systems and discusses a novel data clustering process using constrained ant colony optimization (CACO). They found ACODF performed well in partitioning the data sets for those with clear boundaries between clusters, however, it is less suitable when faced the situation in clusters of arbitrary shape, clusters with outliers and bridges between clusters. To solve these problems, they extend ACO by accommodating a quadratic distance metric, the Sum of K Nearest Neighbor Distances (SKNND) metric, constrained addition of pheromone and a shrinking range strategy to improve data clustering.

Runkler et al. [8] introduced an ant clustering approach that is very close to the original ACO algorithm and at the same time explicitly considers particular clustering models. It is shown how objective function based clustering models such as hard c-means (HCM) and fuzzy c-means (FCM) can be optimized using particular extensions of this simplified ant optimization approach.

4.2. Clustering algorithms based on piling model

As previously mentioned in Section 3, in 1991, Deneubourg et al. [4] et al. proposed the basic model for clustering(BMC). In 1994, Lumer and Faieta [9] introduced the measure of similarity between the data to the BMC, and put forward the LF algorithm, which realized the process of automatic clustering without the need of prior knowledge. Because a great number of following studies are based on the LF algorithm, so it is also known as standard ant colony algorithm (SACA). In this algorithm, Lumer and Faieta define picking up and dropping down probabilities as follows:

\[
P_p(o_i) = \left( \frac{k_1}{k_1 + f(o_i)} \right)^2
\]

\[
P_d(o_i) = \begin{cases} 2f(o_i) & f(o_i) < k_2, \\ 1 & f(o_i) \geq k_2 \end{cases}
\]

\[
f(o_i) = \begin{cases} \frac{1}{s \sum_{o_{j \in \text{neighbours}(o)}} [1 - \frac{d(o_i, o_j)}{\alpha}]} & f(o_i) > 0, \\ 0 & \text{other} \end{cases}
\]

Where \(f(o_i)\) is a measure of the average similarity of data object \(o_i\) with the other data object \(o_j\); \(k_1\) and \(k_2\) are threshold constant variables; \(s\) denotes the neighborhood radius; \(d(o_i, o_j)\) denotes the distance between two objects; \(\alpha\) defines the colony similarity coefficient, which directly affects not only the number of clusters, but also the convergence speed of clustering algorithm. A greater value of \(\alpha\) will result in a larger colony similarity and a faster convergence speed, and vice versa.

Based on this model, Gutowitz [10] introduced the complexity-seeking ants which could sense the complexity (or entropy) in their neighborhood. The entropy was calculated by the presence or absence of objects, so that all-empty or all-occupied neighborhoods have zero complexity (low entropy), whereas checkerboard patterns have the highest complexity. The complexity-seeking ants could speed up the convergence of the clustering task performed by basic ants, because they tend to pick up and drop down objects in regions with high entropy, avoiding useless movement.

Monmarché et al. [11] proposed AntClass algorithm, which is also based on LF model. AntClass allows more than one objects in the same cell, forming heaps of objects. The ants in this algorithm are also able to carry an entire heap of objects. Another important contribution of AntClass is to make use of K-means to improve the convergence of SACA and reduce classification errors.

Ramos and Merelo [12] developed a novel ant-based clustering algorithm called ACLUSTER. The main contribution is that, different from all previous researches, ACLUSTER improves the random move policy to make the algorithm more efficient. The ants of ACLUSTER would move according to transition probabilities that depend on the spatial distribution of pheromone across the environment. Pheromone weighting function is defined as:

\[
W(\sigma) = \left(1 + \frac{\sigma}{1 + \gamma \sigma}\right)^{\theta}
\]
This equation measures the relative probabilities of moving to a grid \( r \) with pheromone density \( \sigma(r) \). The parameter \( \beta \) controls the degree of randomness with which the ant follows the gradient of the pheromone. \( \gamma \) represents the sensory capacity. The transition probabilities on the grid space to go from cell \( k \) to cell \( i \) are given as follows:

\[
P_e = \frac{W(\sigma)w(\Delta_i)}{\sum_{j \neq i} W(\sigma)w(\Delta_j)}
\]  

(13)

where the notation \( j/k \) denotes the sum over all the grids \( j \) which are in the local neighborhood of \( k \). \( w(\Delta_i) \) is another weighting function, where \( \Delta_i \) measures the magnitude of the difference in orientation for the previous direction the last time the ant moved. The pheromone would evaporate with the disappearing of objects in any area. In other words, ACLUSTER provides a swarm mechanism that all ants share a global memory by the pheromone information. Additionally, [12] suggests the use of combinations of two independent response threshold functions, each associated with a different environmental factor such as the number of objects in the vicinity and the similarity.

Handl and Meyer [13] (2002) applied ant-based clustering to online documents classification field. The authors employed ants with different speeds, which are called "inhomogeneous population". Based on Eq.11, the novel similarity function can be expressed as:

\[
f(o_i) = \begin{cases} 
\frac{1}{s^2} \sum_{o_j \in \text{neighbor}(o_i)} \left[ 1 - \frac{d(o_i, o_j)}{s(\alpha(v-1)/V_{\text{max}})} \right] & f(o_i) > 0 \\
0 & \text{other} 
\end{cases}
\]

(14)

where \( v \) is the speed of this single ant; \( V_{\text{MAX}} \) is the highest speed of all the ants. Slower ants can make "fussier" decisions about picking and dropping. Also, they introduce the adaptive scaling strategy and jumping ants to the new approach. A stagnation control is used to solve the outlier problem by setting a failure counter. Finally, in order to reduce time consuming, they introduce the concept of eager ants, which could pick up a new object immediately after dropping their loads.

Hartmann [14] introduced neural network to train both the system's disparity function and move policy. Every single ant has a neural network, taking the objects in its neighborhood as inputs, while returning the move action and the pick up or drop down action as outputs. By adjusting the evolutionary system fitness function, the ants could create annular clusters with hierarchical structure. More precisely, one cluster could surround another.

Vizine et al. [15] presented an adaptive ant-clustering algorithm (\( \lambda \)CA) with a number of improvements to LF model: 1) A cooling scheme for \( P_p \). The value of picking up probability \( P_p(o_i) \) would drop after a certain number of cycles; 2) A variable \( f(o_i) \). A larger similarity value \( f(o_i) \) indicates the existence of a larger, more stable cluster, thus the neighborhood range would increase; 3) Pheromone signals. It would make ants inclined to drop similar objects together, less possible to pick up objects from the area with high-density pheromones.

Kanade and Hall [16] combined AntClass algorithm [11] with the classical FCM. The raw clusters created by AntClass are then refined by FCM. This means that the centroids of each initial cluster formed by AntClass act as initial prototypes for FCM. Then, objects are reassigned to its best matching fuzzy cluster.

Yang and Kamel [17] presented an aggregated clustering approach using multi-ant colonies algorithms. They proposed a model consisting of a queen ant agent and some parallel ant colonies. Parallel ant colonies adopt different moving speed and different versions of the probability conversion function, generating different clustering results to be sent to the queen ant agent. Combined with a hyper-graph model, the queen ant agent calculates a new similarity matrix that would be returned back to each ant colony. Ant colonies would cluster the objects again using the new information fed back from the queen ant agent.
Based on the model, they also give 3 strategies for multi-ant colonies implementation: 1) keeping predecessor strategy; 2) circular exchange strategy; 3) lowest outliers strategy. The experiments show that the average performance of the aggregated multi-ant colonies algorithms is better than that of the single ant-based clustering algorithm and the K-means algorithm.

Fernandes et al. [18] introduced a hybridization clustering approach of Ant System and Kohonen Self-Organizing Maps (Kohonen’s SOM). The approach considers each data object as an ant, which moves inside a grid changing the cells it goes through, in a fashion similar to Kohonen’s SOM. Experiments demonstrate that KohonAnts model is useful for clustering tasks, showing very satisfying results on some benchmark problems.

4.3. Summary of research emphasis

By reviewing the existing literatures, we can summarize the current research emphasis on ant colony clustering algorithms. Based on the foraging model, a lot of works focus on the integration of ACO and other clustering algorithms. Also, some works use the ants with special functions to solve clustering problems. While most works inspired by piling behavior are based on LF model. The main directions of these researches involve combining with other clustering algorithms, improving moving policy, improving the picking and dropping probability functions, using different overall strategies and using different attributes (e.g. using entropy). All the analysis results are shown in Figure 4.

![Figure 3. Queen ant agent/ant colony model for parallel multi-ant colonies [17]](image)

![Figure 4. Current research emphasis on ant colony clustering algorithms](image)
5. Applications

Ant colony clustering methods have been extensively applied in many fields, such as gene expression, medicine, customer relationship management (CRM), information security, image analysis, web mining, etc.

We classify and summarize the contributions on applications of ant colony clustering methods in detail. And it is shown in Table 3.

<table>
<thead>
<tr>
<th>Fields</th>
<th>Specific directions</th>
<th>Main literatures distributions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Information technology</td>
<td>Web mining</td>
<td>Document mining [12-15], topic discovery, web usage mining and information retrieval [12]</td>
</tr>
<tr>
<td></td>
<td>Information security</td>
<td>Intrusion detection system, network security model, network traffic analysis and computer forensics</td>
</tr>
<tr>
<td></td>
<td>Wireless sensor networks</td>
<td>Data dissemination and routing protocol</td>
</tr>
<tr>
<td></td>
<td>Image processing</td>
<td>Image retrieval, image analysis and image segmentation</td>
</tr>
<tr>
<td>Biology</td>
<td>DNA analysis</td>
<td>DNA chip analysis</td>
</tr>
<tr>
<td></td>
<td>Gene expression</td>
<td></td>
</tr>
<tr>
<td>Medicine</td>
<td>Electrocardiogram analysis</td>
<td>Electrocardiogram interpretation</td>
</tr>
<tr>
<td></td>
<td>Medical image analysis</td>
<td>Medical image segmentation</td>
</tr>
<tr>
<td>Business</td>
<td>Solvency prediction</td>
<td>Solvency Prediction model</td>
</tr>
<tr>
<td></td>
<td>CRM</td>
<td>Customer segmentation</td>
</tr>
<tr>
<td>Transport</td>
<td>Highway planning</td>
<td>Macroscopic planning</td>
</tr>
</tbody>
</table>

Table 3 lists the main applications of ant colony clustering algorithms, but we believe that this has not included all the work, because the ant colony clustering methods are being applied in various fields widely and deeply.

6. Conclusions and future works

In this paper, ant colony clustering methods are completely analyzed from the perspective of models, algorithms and applications. We present that most ant colony clustering algorithms are based on “foraging model” and “piling model”. These algorithms contribute to this field with various creative points and this paper reviews the main innovated and improved approaches. The research of these algorithms can be applied in many fields, including information technology, biology, medicine, etc.

It is clear that the development of colony clustering algorithms research is a major achievement of data mining and swarm intelligence, but the related research is still in its infancy and there are many new directions need to be investigated. In our opinions, future works could focus on self-adaption of the initial parameters to make algorithms more unsupervised, and the ant colony clustering methods can be also applied to the dynamic data clustering. In addition, many new applications need to be discovered in this field.
7. Acknowledgement

This work is supported by National Basic Research Program of China (973 Program) (2007CB311203), the Fundamental Research Funds for the Central Universities (BUPT2010PTB0501, BUPT2010PTB0502), and the Key Project of Chinese Ministry of Education (no code number).

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