

EVALUATING THE POTENTIAL OF ANT COLONY OPTIMIZATION IN CLUSTERING OF LIDAR DATA

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Abstract. LIDAR technology has become a standard tool for collecting 3D data from complex surface of 3D object such as building and tree in urban area. There is a wide range of investigation in extracting different man made or natural objects from dense LIDAR data. Practice shows for extracting information from massive point in complex surface, some clustering processes are required for grouping LIDAR data. Referring to density and complexity of LIDAR data, conventional clustering methods are not appropriate enough. Recently several bio-inspired clustering techniques are proposed to overcome drawback of traditional methods. One of the main categories of these techniques which inspired by the social behavior of living organism is ant colony optimization. In this paper, three clustering algorithms based on ant colony optimization are proposed and their results compares with traditional k-means method. These techniques are based on Foraging behavior and Cemetery organization of ant colony. Foraging based clustering and cemetery organization algorithm results demonstrate considerable improvement in quality of clustering result. Referring to the ability of the ant colony optimization to perform local and global search simultaneously, these algorithms can find global optimum in clustering of dense and complex LIDAR data. The main advantage of cemetery organization algorithm is ability to work even when cluster number is unknown. By hybridization of foraging behavior and k-means, the quality of clustering result and processing time become much better than other techniques.

Keywords: Clustering, Ant Colony Optimization, LIDAR, Foraging, Cemetery Organization

1 Introduction

LIDAR (Light Detection And Ranging) technology has become an effective tool for collecting 3D data from complex surfaces such as urban area [27]. These data are the bases of a wide range of application such as 3D city modeling, urban management and telecommunication [9, 22, 27, 36, 37]. Practice shows that the variety of 3D objects and the massive amount of points require introducing some level of organization into the data before the extraction of information can become effective in several applications [9, 36]. Such organization involves aggregation points with similar features into segments [16]. Different algorithms are proposed for segmentation and clustering of LIDAR data [3, 16, 29, 30].

During last years, several algorithms are proposed to solve clustering problem [2, 6, 17, 38]. These algorithms can be divided into five classes: partitioning methods, hierarchical methods, density based methods, grid based methods and model based methods [2]. In the context of 3D object extraction from LIDAR data in urban area, various type of information, such as first and last range and intensity data has been fused to overcome the difficulties of clustering and identification of complicated objects. Collecting this information, extremely enlarge the size of data sets and proportionally the dimension of feature spaces in clustering process [30]. As a result, most of traditional clustering techniques that have been applied properly in other applications with standard data and limited feature space dimension are not efficient enough for object extraction process from LIDAR data [29, 30].

Recently, several bio-inspired solutions are proposed to overcome the problems of traditional clustering methods [1, 5, 14, 15, 20, 33]. Swarm intelligence is one of these techniques that inspired from self organized colonies in the nature such as ant colonies behaviors in foraging or cemetery organization, bee colonies behaviors in foraging or mating, flocking of bird and schooling of fish [13, 21, 25]. Swarm intelligence, models such behaviors then uses these models to solve several real world problems, such as clustering, planning, scheduling, etc [13]. Recently, several researches focus on developing clustering methods based on particle swarm optimization [14, 24], artificial bee colony [15, 26] and ant colony optimization [18]. There is a wide range of investigation on clustering with ant algorithm that shows effectiveness and popularity of ant based clustering [13, 18, 19, 20, 28, 31, 39].

Referring to high potential of ant based clustering techniques, in this paper the potential of this group of swarm based optimization techniques will be evaluated on clustering of LIDAR data in an urban complex area.

2 Ant Colony Optimization

Ant colony optimization is inspired from complex behavior which is observed in ant colonies [12]. Ant colonies consist of simple ants that have no special intelligence. Their group is decentralized and self-organized but several complicated behaviors are observed in this simple group [12]. Studies show complex behaviors emerge from indirect communication exist between agents which are called stigmergy. In this way, ant change environment for interacting and based on information perceived from environment, performs a simple, basic action [13]. Two main collective behaviors that have been studied widely in ant colonies are Foraging behavior and Cemetery Organization.

- **Foraging behavior** is ability of ants to find the shortest path between their nest and food [12]. Interaction between ants is done by pheromone which each ant after finding food, on its way to nest, lays it on trail. Other ants prefer to move on the path with more pheromone. These stigmergy and simple rule, cause ants to convergent to shortest path to food source. There are several algorithms which try to model this behavior such as: Simple Ant Colony Optimization (SACO) [12], Ant System (AS) [12], Ant Colony System (ACS) [7], Max-Min Ant System [32], etc. In this paper we use ACS, because it has a general transition rule and consider exploitation and exploration in contrast of other algorithms which neglect exploitation. Suppose k^{th} ant currently located at i^{th} node, for moving to next node j , it use transition rule that is mentioned in EQ (1) and select next node for rest of its way.

$$j = \begin{cases} \arg \max_{u \in N_i^k} \{ [\tau(i, u)]^\alpha [\eta^k(i, u)]^\beta \} & \text{if } q \leq q_0 \\ S & \text{otherwise} \end{cases} \quad (1)$$

Where N_i^k is a set of valid nodes to visit, τ is pheromone density on link between i and u ; η is heuristics information that is proportional to inverse of distance between i and u ; $q_0 \in (0, 1)$ is a constant parameter which is trade off between exploration and exploitation; α, β are constant which determine the weight of pheromone and heuristics information, respectively; q is a random number between 0 and 1, and S is node randomly selected according to probability of each node which probability of moving ant to u^{th} node, can be calculated according to EQ (2).

$$P^k(i, u) = \frac{[\tau(i, u)]^\alpha [\eta^k(i, u)]^\beta}{\sum_{j=1}^K [\tau(i, u)]^\alpha [\eta^k(i, u)]^\beta} \quad (2)$$

When each ant visits all nodes and completes its solution, according to quality of solution, best ants are selected and only best ants are allowed to reinforce pheromone concentration on the links of the corresponding best path. EQ (3) show how pheromone is update.

$$\tau_{ij}(t + 1) = (1 - \rho)\tau_{ij}(t) + \sum_{l=1}^L \Delta\tau_{ij}^l \quad (3)$$

Where ρ specifies rate of pheromone evaporation and $\Delta\tau_{ij}^l$ is amount of pheromone adds to link i - j by best ant and L is the number of best ants.

This process repeat until termination criteria is satisfied. Termination criteria can be: maximum number of iteration, when accepted solution has been found or when all ants (or most of the ants) follow the same path. As a final solution, best ant in all iterations or a solution that all ants are convergent to that can be selected [13].

- **Cemetery Organization** is another collective behavior of ants which ants exhibit clustering behavior in collecting corpse [8, 11, 13]. Ants during cleaning their nest collect corpse on its way and put them together, so clusters of corpse are made. Each ant seems to behave individually, moving randomly in space while picking up or dropping corpse. The decision to pick up or drop a corpse is based on density of object in its neighborhood. This simple behavior of ants results in

the emergence of a more complex behavior of cluster formation [13]. Cemetery organization algorithms are basically designed by considering the concept of a 2D grid where data are laid at random and then automatically organized. A set of ant-like agents is allowed to move in random direction through the grid, picking up and dropping data based on their similarity degree within a certain neighborhood. Another clustering behavior observed in ant colonies is brood sorting [13]. Where larvae are sorted in such a way that different brood stages are arranged in concentric rings. Smaller larvae are located in the center, with larger larvae in periphery so the concentric clusters organized. It is clear by modeling these behaviors; it can be employed directly to real world clustering application.

3 Clustering of LIDAR Data Using Ant Colony Optimization

Ant based clustering in compare of conventional clustering methods, is much more reliable and may overcome the shortages of traditional algorithms such as trapping in local optimum [18, 20, 31]. Clustering with ant algorithms can be robust and effective tool for clustering complex space because ant algorithms is a population based algorithms which ants can search space completely and find global optimum. By employing ant algorithms in clustering problem, we can benefit the ant algorithm such as: robustness, effectiveness, finding global optimum.

Referring to two collective behaviors of ant colonies (i.e. Foraging behavior and Cemetery Organization), several different clustering techniques have been developed based on these two behaviors of ant colonies [8, 18, 31]. In the first method, for using foraging behavior, recast clustering as an optimization problem then implement foraging algorithm to explore global optimum solution. In the second case, use Cemetery Organization algorithm directly for clustering problem because the algorithms mimic the clustering behavior in ant colonies and only data is changed.

3.1 Clustering with Ant Foraging Behavior

There are two scenarios for applying foraging behavior in clustering problem: using ACS for finding global optimum in clustering as an optimization problem and hybridization of ACS and k-means. For both of them we should reformulate clustering as an optimization problem and then employ ant foraging algorithm to discover optimum solution for clustering.

- **Foraging based algorithm:** This technique can work based on minimization of the sum of squared distance from the mean within each cluster or maximization of separation between cluster centres. We use sum of squared distance from the mean within each cluster as an objective function:

$$F(w, m) = \sum_{j=1}^K \sum_{i=1}^E \sum_{v=1}^P w_{ij} \|x_{iv} - m_{jv}\|^2 \quad (4)$$

Where v is number of feature indicator, i shows data number, j indicates cluster number; x is data vector; m is cluster center and w_{ij} is weight of belonging i^{th} data to j^{th} cluster. Consider E data with P features that our goal is portioning them into K cluster. Represent problem with $E \times K$ nodes, which each row represent a data and columns shows cluster, ants are allowed to visit only one node in each row and also only each row once. By moving on the nodes, ants cluster data. By placing ant on each node, it means in ant solution, corresponding data is assigned to a cluster correspond to column of node. At each data, ant uses EQ (1) for selecting cluster which pheromone is available on nodes and heuristic information is computed by distance from each cluster center. After that ant goes to another data randomly and it uses Tabu list to prevent visiting a data more than one. After visiting all data and completing the solution, by EQ (4) evaluation the quality of each ant solution is done. According to their fitness, best ants which have less fitness value are selected and their paths are reinforced by EQ (3). This process is repeated until a termination criterion is satisfied.

- **Hybridization of ACS Foraging algorithm with k-means.** Ant foraging behavior is a robust algorithm and finds global optimum in clustering problem but it has slow convergence rate. On the other hand, k-means are fast and simple but quality of this algorithm depends on initial cluster center and may trap in local optimum. It seems by combining them, hybrid algorithm can

overcome shortages of both methods and algorithm become fast and robust. There are several literatures that combine this two method together in different ways [19, 28, 39]. Proposed method starts by choosing the number of clusters and a random initial cluster center for each cluster. ACS plays its part in assigning each pixel to a cluster. We can summarize algorithm in these steps: first initialization phase and setting parameter is done. Then for each ant, K cluster center randomly is selected. Next step is assigning data to cluster by foraging behavior which is done by pheromone and heuristics information according to EQ (1). After assigning all data, new cluster center is calculated; with new cluster center assigning data to cluster is repeated until new cluster center convergent to old ones. For all ants this process is done and then solution of each ant is evaluated by EQ (4), then best ants are selected. Only best ants are used to update pheromone by EQ (3). Continue algorithm until the termination criterion is satisfied [28]. In this method several ant work together and each of them start with different initial center and these cluster center can distribute over search data. Using concept of k-means make algorithm fast and overcome problem of ant foraging behavior clustering that is time consuming.

3.2 Clustering with Ant Cemetery Organization Behavior

The basic idea in this method is inspired directly from Cemetery Organization which observed in real ant colonies [8, 11, 13]. Simulating of this behavior is done by scattering data on a 2D grid, each cell contain only one item. Then distribute ants randomly on the grid. Each ant moves in random direction and by local information from environment decides to pick up or drop items. Consider each ant can carry only one item. At each time step if ant is loaded try to drop it in a cell which items in its neighborhood is similar to the load. In contrast, if ant is unloaded try to pick up an item when it is dissimilar to its neighbors. Now we discuss this model in more detail. In this model, 2D grid is considered and all data and ants randomly place on it. Then ants start to move in a random direction, if ant is free (unloaded) and faces to an item on grid, calculate similarity between that item and its neighbor, by EQ (5) it computes the probability of picking it up.

$$p_p(y_a) = \left(\frac{\gamma_1}{\gamma_1 + \lambda(y_a)} \right)^2 \quad (5)$$

Where y_a is item that ant faces to it, γ_1 is constant, $\lambda(y_a)$ is density of item in its neighborhood and $p_p(.)$ is the probability of picking item up. Intuitively, if density of data is low in its neighbor (i.e. it is not similar to its neighbors), with high probability ant decide to pick it up, otherwise, when item is similar to neighbors, probability of pick item up is low. Another state is when ant carries an item. In this situation, ant moves by its step size when it reaches free cell, ant computes similarity of its load and its neighborhood and according to EQ (6) decide to drop it or continue its way.

$$p_d(y_a) = \begin{cases} 2\lambda(y_a), & \lambda(y_a) < \gamma_2 \\ 1, & \lambda(y_a) \geq \gamma_2 \end{cases} \quad (6)$$

Where y_a is an item that is carried by ant, γ_2 is constant parameter and $p_d(.)$ is the probability of dropping item. Parameter γ_2 works as a threshold, if similarity of load with ant neighbors is more than threshold ant certainly drop it, otherwise the probability of dropping by EQ (6) is computed. If item which is carried by ant is dissimilar to neighbors, probability of dropping becomes less.

Ants continue moving, picking up and dropping by above rules. After maximum iteration, algorithm stops and result can be evaluated. In this algorithm there are several parameters have to be set, such as: grid size, number of ants, local density, and neighborhood size. These parameters have direct effect on convergence of solution. Boryczka suggest some relation between number of data and value of parameter [8]. There are several modifies to this algorithm, it uses some change like: different moving speed, short term memory, different distance memory, different pick up or dropping probability, etc [13].

4 Experimental Investigations

The airborne LIDAR data used in our experimental investigations have been recorded with TopScan's Airborne Laser Terrain Mapper system ALTM 1225, [35]. The data are recorded in area of Rheine in

Germany. Two different patches with residential and industrial pattern were selected in the available dataset. The selected areas were suitable for the evaluation of the proposed clustering strategy because the required complexities (e.g. proximities of different objects: building and tree) were available in Figure.1. a, b. The pixel size of the range images is one meter per pixel. This reflects the average density of the irregularly recorded 3D points which is fairly close to one per m². Intensity images for the first and last pulse data have been also recorded and the intention was to use them too in the experimental investigations. Figure.1 shows first and last pulse range images from the Rheine area. The first step in every clustering process is to extract the feature image bands. The properties of these feature bands should carry useful textural or surface related information to differentiate between regions related to the surface. Several features have been proposed for clustering of range data. [4, 23]. In the following experiments we restrict to five types of features: LIDAR range data; The ratio between first and last pulse range images; Top-Hat filtered last pulse range image; Local height variation which is computed using a small window (3*3) around a data sample and Last pulse Intensity

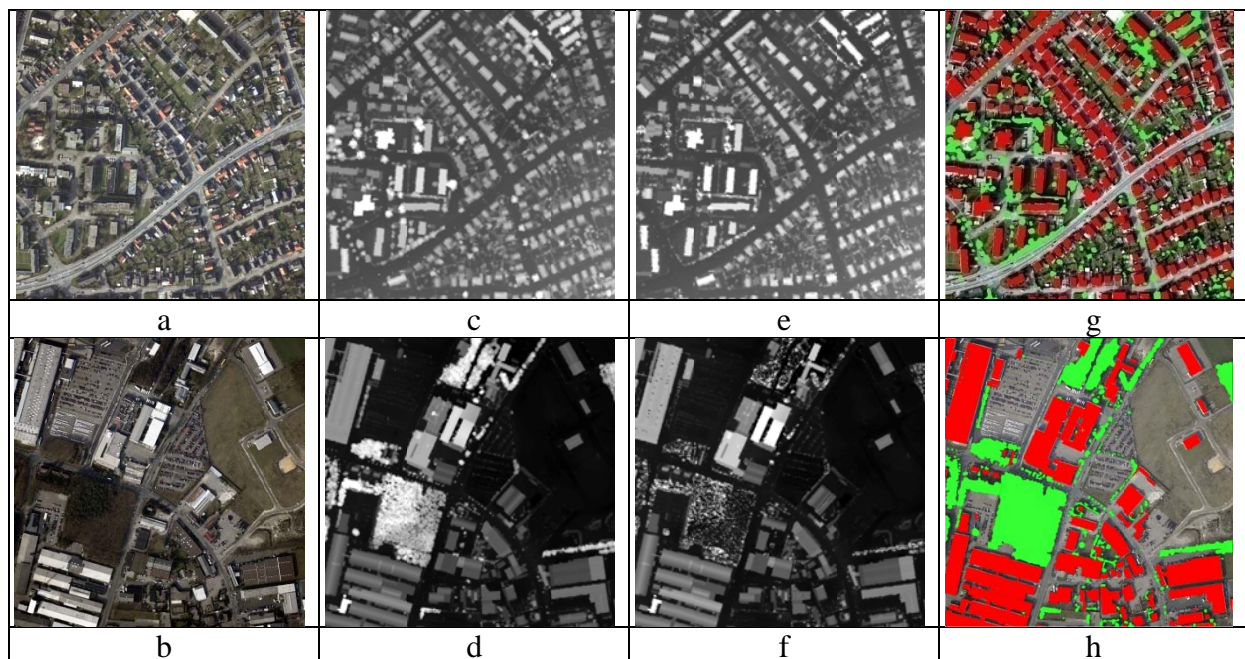


Fig. 1. a) Aerial image of residential evaluation area. b) Aerial image industrial evaluation area. c) First LIDAR range data of residential area. d) First LIDAR range data of industrial area. e) Second LIDAR range data of residential area. f) Second LIDAR range data of industrial area. g) Overlaid manual digitization objects in residential area. h) Overlaid manual digitization objects in industrial Area

According to three proposed algorithms, the following values considered for clustering of LIDAR data in both of residential and industrial area. (Table 1.)

Table 1. Parameters used in clustering of LIDAR data

| Algorithm | Parameters | Value |
|------------------------------|----------------------|---------|
| Foraging algorithm | Number of ants | 100 |
| | Number of best ants | 10 |
| | Number of iterations | 100 |
| Cemetery Organization | Number of ants | 150 |
| | Grid size | 500*500 |
| | Neighborhood size | 5*5 |

The output of applied four algorithms for clustering of the data sets into three clusters (ground, tree, and building) is depicted in Figure 2. Figures (2a) to (2d) show the clustering result of k-means (KM), Foraging based clustering, hybridization of foraging and k-means and Cemetery Organization algorithms in residential area, respectively. Building class regions are highlighted in red and vegetation class regions in green color. Figures (2e) to (2h) show the clustering result of k-means (KM), Foraging based clustering, hybridization of foraging and k-means and Cemetery Organization algorithms in industrial area, respectively

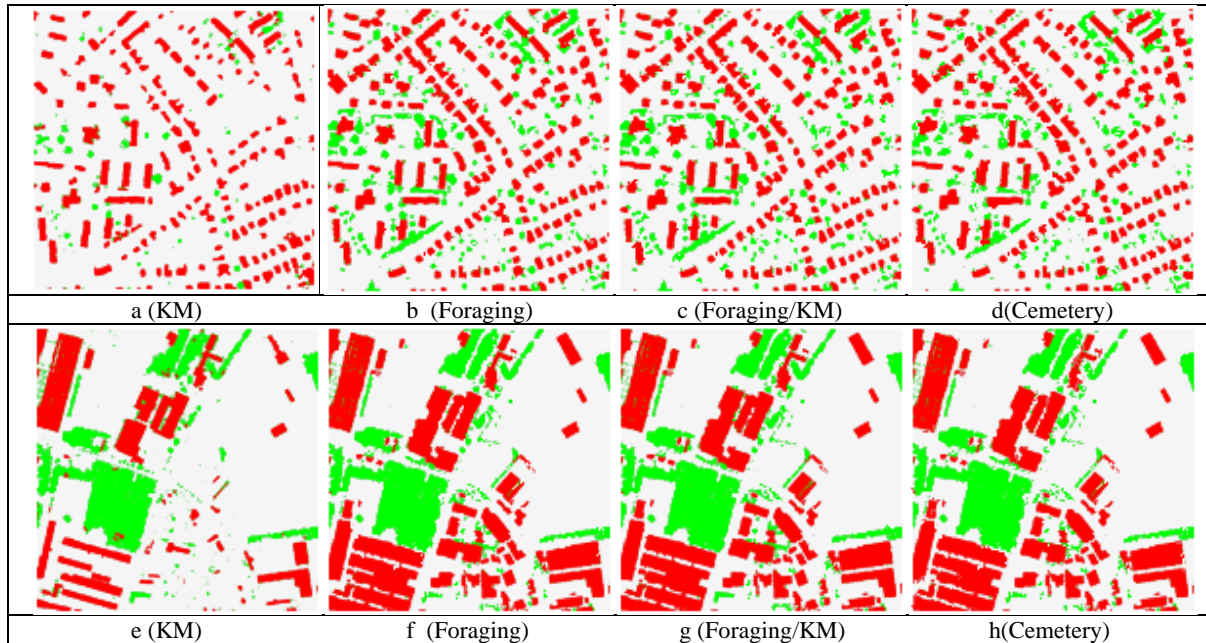


Fig. 2.. Clustering results of different techniques in residential and industrial area

4.1 Accuracy Assessment

Comparative studies on clustering algorithms are difficult due to lack of universally agreed upon quantitative performance evaluation measures. In this paper, confusion matrix used to evaluate the true labels and the labels returned by the clustering algorithms as the quality assessment measure. Given some ground truth the relation between the "true" classes and the classification result can be quantified. With the clusters the same principle can be applied. Mostly a much bigger number of clusters is then related to the given ground truth classes to examine the quality of the clustering algorithm. From the confusion matrix we calculate the *Kappa Coefficient* [10]. The accuracy measurements showing above, namely, the overall accuracy, producer's accuracy, and user's accuracy, though quite simple to use, are based on either the principal diagonal, columns, or rows of the confusion matrix only, which does not use the information from the whole confusion matrix. A multivariate index called the Kappa coefficient has found favor [34]. The Kappa coefficient uses all of the information in the confusion matrix in order for the chance allocation of labels to be taken into consideration. The Kappa coefficient is defined by:

$$\hat{k} = \frac{N \sum_{i=1}^r x_{ii} - \sum_{i=1}^r (x_{i+} \times x_{+i})}{N^2 - \sum_{i=1}^r (x_{i+} \times x_{+i})} \quad (7)$$

In this equation, \hat{k} is the Kappa coefficient, r is the number of columns (and rows) in a confusion matrix, x_{ii} is entry (i, i) of the confusion matrix, x_{i+} and x_{+i} are the marginal totals of row i and column j , respectively, and N is the total number of observations [34].

Table 2 shows the confusion matrix and Kappa coefficient of k -means and three proposed algorithms clustering in residential dataset. The Error matrix and Kappa coefficient of k -means and proposed algorithms clustering in industrial dataset presented in Table 3.

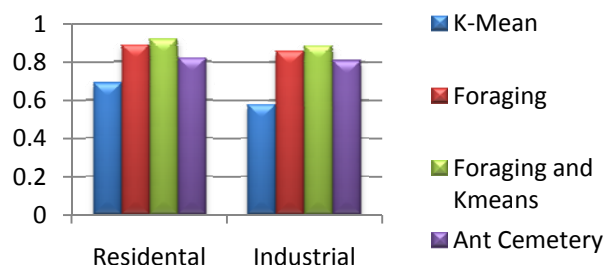
Table 2. Confusion matrix and Kappa coefficient of k-means (KM), Foraging based clustering, hybridization of foraging and k-means and Cemetery Organization algorithms in residential area.

| | | Reference Data | | | | | Reference Data | | | | |
|----------------------------|----------|----------------|-------|--------|---------------------------|---------------|----------------|--------|--------|--------|--------|
| | | Building | Tree | Ground | Total | | Building | Tree | Ground | Total | |
| KM | Building | 64388 | 1551 | 338 | 66227 | Foraging / km | Building | 115302 | 3316 | 4486 | 123759 |
| | Tree | 3561 | 58692 | 5930 | 68183 | | Tree | 1823 | 61533 | 4889 | 69391 |
| | Ground | 54341 | 10509 | 290740 | 355590 | | Ground | 3815 | 7303 | 31006 | 42124 |
| | Total | 122240 | 70752 | 297008 | 490000 | | Total | 120940 | 72152 | 296908 | 490000 |
| Kappa coefficient = 0.6927 | | | | | Kappa coefficient = 0.919 | | | | | | |
| | | Reference Data | | | | | Reference Data | | | | |
| | | Building | Tree | Ground | Total | | Building | Tree | Ground | Total | |
| Foraging | Building | 115268 | 3138 | 5353 | 123759 | Cemetery Org | Building | 115506 | 3019 | 5234 | 123486 |
| | Tree | 1896 | 61579 | 5916 | 69391 | | Tree | 1759 | 61595 | 5779 | 69122 |
| | Ground | 3969 | 7303 | 285588 | 296850 | | Ground | 4091 | 7435 | 285324 | 296432 |
| | Total | 120940 | 72152 | 296908 | 490000 | | Total | 120363 | 72392 | 296845 | 490000 |
| Kappa coefficient = 0.886 | | | | | Kappa coefficient = 0.812 | | | | | | |

Table 3. Confusion matrix and Kappa coefficient of k-means (KM), Foraging based clustering, hybridization of foraging and k-means and Cemetery Organization algorithms in residential area.

| | | Reference Data | | | | | Reference Data | | | | |
|---------------------------|----------|----------------|-------|--------|---------------------------|---------------|----------------|-------|--------|--------|--------|
| | | Building | Tree | Ground | Total | | Building | Tree | Ground | Total | |
| KM | Building | 26878 | 2168 | 1108 | 30154 | Foraging / km | Building | 40582 | 631 | 1568 | 42931 |
| | Tree | 187 | 3707 | 105 | 3999 | | Tree | 36 | 17258 | 487 | 17721 |
| | Ground | 16443 | 12879 | 139025 | 168347 | | Ground | 2678 | 2510 | 136570 | 141768 |
| | Total | 43508 | 18754 | 140238 | 202500 | | Total | 43342 | 18767 | 140229 | 202500 |
| Kappa coefficient = 0.584 | | | | | Kappa coefficient = 0.893 | | | | | | |
| | | Reference Data | | | | | Reference Data | | | | |
| | | Building | Tree | Ground | Total | | Building | Tree | Ground | Total | |
| Foraging | Building | 39846 | 999 | 1938 | 42223 | Cemetery Org | Building | 39822 | 944 | 1950 | 42783 |
| | Tree | 482 | 16354 | 932 | 17294 | | Tree | 581 | 16157 | 1032 | 17770 |
| | Ground | 3010 | 2642 | 136304 | 141823 | | Ground | 3053 | 2694 | 136200 | 141947 |
| | Total | 44209 | 20282 | 138009 | 202500 | | Total | 44008 | 20133 | 138349 | 202500 |
| Kappa coefficient = 0.863 | | | | | Kappa coefficient = 0.813 | | | | | | |

By comparing the counts in each class a striking difference to the ant based algorithms result has to be observed. For the two classes of major interest in this study, the Building class and Tree class, the differences are quite significant (Figure 3). In all of ant based techniques we had a significant improvement referring to the traditional k-mean method. There are also some differences in the potential of ant based methods in clustering of the LIDAR data. The best situation in both of accuracy and computation times is related to the Foraging and K-means method. About the Ant cemetery method, although we got a good accuracy performance by applying this method, but the convergence of commutation is so slow and it needs a large number of iteration for doing the clustering process.

**Fig. 3.** The value of Kappa coefficient, in four situations of clustering by k-mean and three proposed algorithms.

Nevertheless, the potential of Ant based techniques is completely dependent to the value of their parameters. In this paper, the optimum value of these parameters determined based on a trial and error process by an expert operator.

5 Conclusion

This paper presented the capability of ant based optimization methods in clustering of LIDAR data. By modeling foraging and cemetery organization behavior of ant colony and implementation of them in clustering problem, we improved the clustering potential in the complex urban area. Important note in using ant colony optimization for clustering problem is optimum determination of parameters which have direct effect on efficiency of computation. By choosing appropriate parameters value, ant based algorithms may obtain much more reliable and efficient results in comparing of other traditional clustering methods. As finding the optimum parameters of ant colony optimization is time consuming and dependent to the skill of expert operator, further investigations need for automatic determination of ant colony optimization's parameters.

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