

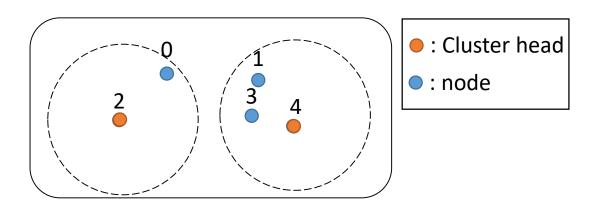
Optimized node clustering by using genetic algorithm

Haoran Mei Dec, 2021

- Introduction
- **❖** System model
- **❖**Simulation result
- *****Conclusion

- Introduction
- *System model
- **Simulation** result
- *Conclusion

- Trajectory planning for UAV assisted data collection
 - ☐ Two general steps
 - ➤ Cluster head election based node clustering
 - Cluster head (CH) identification → Group the nodes within the region of a CH as a cluster
 - Cluster heads should collect data from nodes with their own region and deliver them to the UAV.
 - ➤ Path planning
 - Shortest tour that passes through all cluster heads. (TSP)



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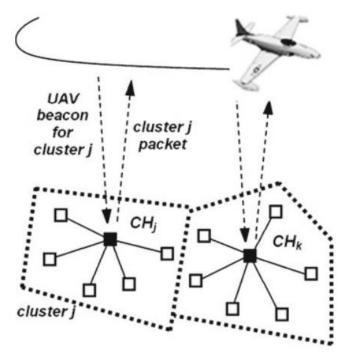
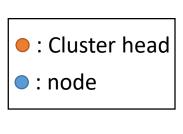
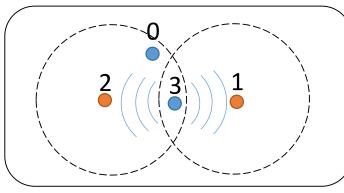


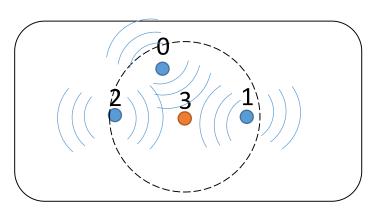
Fig. 2 Basic scheme for cluster-based UAS data collection

- Problem definition
 - \square Given a set $\mathbf{D} = \{d_1, \dots, d_K\}$ of K nodes
 - \triangleright Group them into N clusters with N < M, where M is a given integer.
 - ☐ Basic assumption
 - It is allowed that a node is covered by multiple cluster heads.
 - The UAV would receive redundant data, since the node transmit data to adjacent CHs by broadcasting.
 - The region defined by the CH = The communication range.
 - >It is desirable to have as few clusters as possible.
 - This could alleviate the degree of overlap

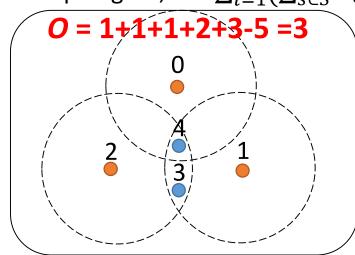


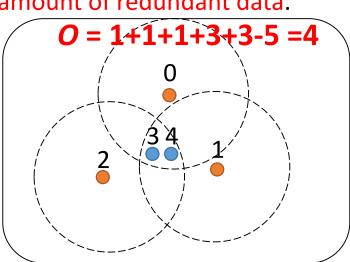


Minimize # of clusters



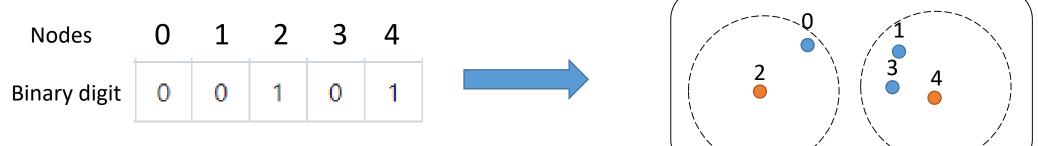
- ❖ Node clustering
 - ☐Set cover problem with additional goal
 - Figure 3 Set $I = \{1, ..., K\}$ of integers and a collection $S = \{\{1\}, ..., \{1,3, ..., K\}\}$ of sets whose union is I
 - *I = D, S =* potential cluster configurations.
 - ➤ Goal: identify a smallest sub-collection of **S** whose union is **I**
 - Minimizing the # of clusters which can cover all nodes.
 - Extra goal: if multiple feasible solutions ==> chose the one with minimal overlap degree.
 - Overlap degree, $O = \sum_{i=1}^{K} (\sum_{s \in S} 1\{i \in s\}) K$: The amount of redundant data.
- : Cluster head
- : node





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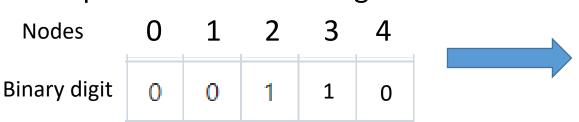
- Model description
 - \square Representation (K nodes)
 - >K bit binary digit.
 - ✓ i-th bit: the binary value implies whether the corresponding node is the cluster header

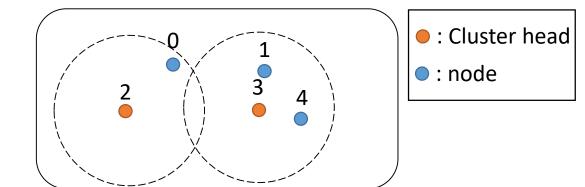


• : Cluster head

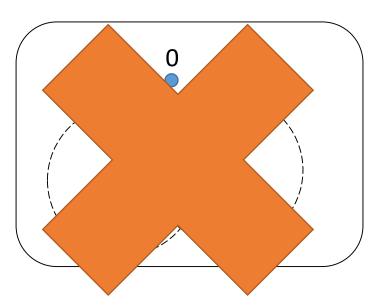
• : node

- **□**Operators
 - ➤ Change the binary values in the digit.
 - >Group the nodes according to the result.



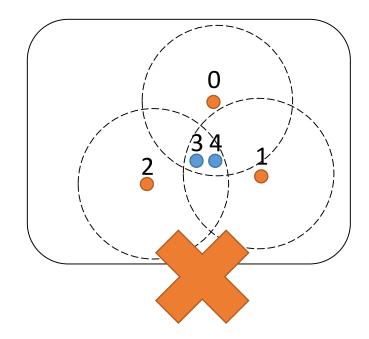


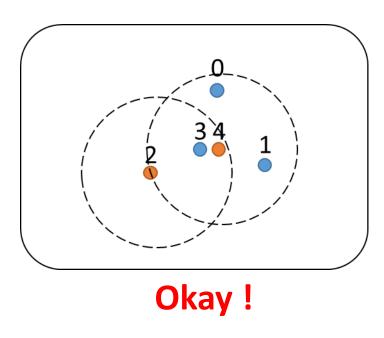
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 - ☐ Fitness function
 - The priority for this problem.
 - P1: Ensure that all *K* nodes are grouped



- Model description
 - ☐ Fitness function
 - The priority for this problem.
 - P1: Ensure that all K nodes are grouped
 - P2: Ensure that number of the generated clusters, N, is less than or equals to M

When M = 2





- Model description
 - ☐Fitness function
 - The priority for this problem.
 - P1: Ensure that all K nodes are grouped
 - P2: Ensure that number of the generated clusters, N, is less than M
 - P3: Minimize the number of clusters
 - P4: Minimize the degree of overlap

of ungrouped nodes

```
The set of clusters
-\operatorname{error} * K^{3}, \quad if \operatorname{error} > 0
fitness = \begin{cases} -(|C| - M) * K^{2}, & if \operatorname{error} = 0, |C| \geq M \\ -(|C| * K + O), & if \operatorname{error} = = 0, |C| < M \end{cases} P2
-(|C| * K + O), \quad if \operatorname{error} = 0, |C| < M P3 & P4
```

The degree of overlap

```
# calculates the fitness
def calculateFitness(self, M):
   if self.error > 0:
        self.fitness = 0 - self.error * (K ** 3)
   elif self.num_cluster > M:
        self.fitness = (M - self.num_cluster) * (K ** 2)
   else:
       cluster_fit = self.num_cluster * K
        self.fitness = 0 - (cluster_fit + self.overlap)
```

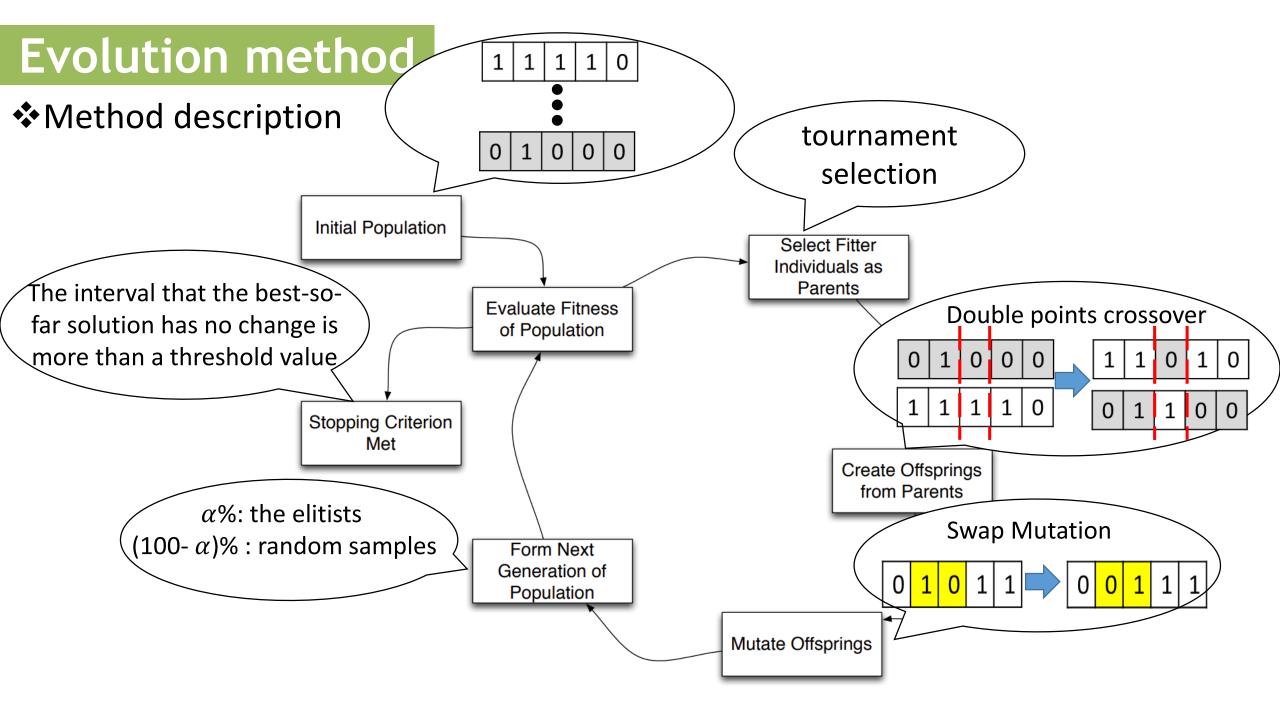
Problem formulation

$$\max_{C^*}$$
 fitness:

$$fitness = \begin{cases} -\operatorname{error} * K^{3}, & if \operatorname{error} > 0 \\ -(|C| - M) * K^{2}, & if \operatorname{error} == 0, |C| \ge M \\ -(|C| * K + O), & if \operatorname{error} == 0, |C| < M \end{cases}$$
P3 & P4

$$O = \sum_{n_j \in D} \sum_{c_i \in C} 1\{\|n_j - c_i\| \le r\} - |\mathbf{D}| \quad \text{The degree of overlaps}$$
 error
$$= \sum_{n_j \in Node} 1\{\sum_{c_i \in C} 1\{\|n_j - c_i\| \le r\} == 0\} \quad \text{# of ungrouped nodes}$$

The radius of the region defined by CH



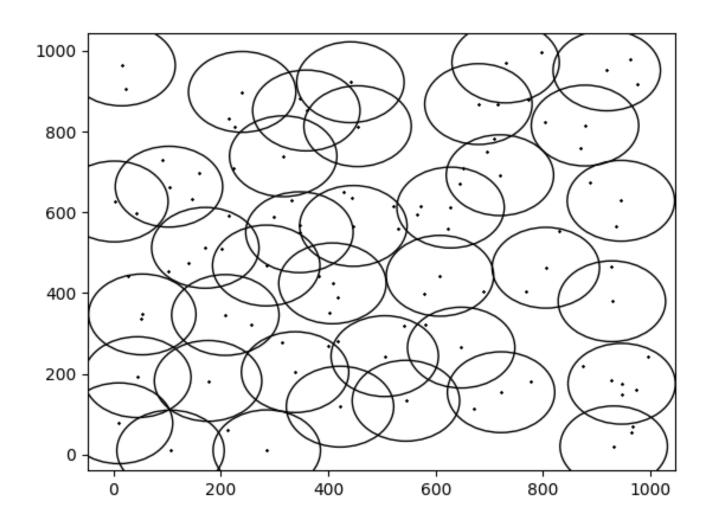
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Parameter configuration

K = 100 # The number of nodes, cannot be change
M = 50 # The required number of cluster
a = 0.5 # alpha: the ratio of the elitist to the next generat
pro_mutation = 0.2 # The probability of executing mutation
size_pop = 1000 # The size of population for each generation
round_crossover = int(size_pop/4) # The rounds of crossover
r = 100 # The radius of cluster region
max_interval = 500 # The maximum interval between old and new

Parameters	Values	Notice or Range
The number of nodes	100	Should be fixed
The required number of clusters	50	1 ~ 100
-alpha	0.5	0 ~ 1
The probability of mutation	0.2	0 ~ 0.5
The size of population	1000	1000 ~
The rounds of crossover	250	250 ~ 1000
The radius of the region defined by each CH	100	Fixed
The threshold on the interval that best-so-far solution has no change	500	200 ~ 1000 (empirical test)

Example of clustering result



❖To see the impact of probability of mutation (max_interval = 200)
□The mutation could more or less speed up the convergence process
□No significant change in the fitness.

Drobability of	Result (running 20 times for the same initial pop)		
Probability of mutation	average # of generation	average opt fitness	average time cost (second)
0 (Only crossover)	521.7	-3779.05	174.925
0.1	531.1	-3776.6	174.29375
0.2	512.1	-3794.35	157.1421875
0.3	509	-3794.05	152.21953125
0.4	548.7	-3783.8	162.134375
0.5	503.75	-3779.15	134.6125

- To see the impact of alpha (max_interval = 200)
 - ☐ Elitists selection has a positive effect on finding a better fitness.
 - ☐ Speed up the convergence process

alpha	Result (running 20 times for the same initial pop)		
(The ratio of the elitists to the next generation of population)	average # of generation	average opt fitness	average time cost (second)
0 (random selection)	779.25	-4197.65	421.65
0.2	579.05	-3794.75	197.26
0.4	554.4	-3789.2	168.8671875
0.6	534.75	-3794.15	155.59
0.8	537.35	-3798.8	152.44
1 (elitists selection)	540.35	-3783.95	152.58

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Conclusion

- *Combinatorial problem?
 - ☐To check it
 - > Definition: Search an optimal solution from a finite solution space.
 - >Characteristic:
 - In most cases, exhaustive search is not tractable.
 - ✓ The size of solution space: 2^K (The # of possible K-bit binary digits)
 - The domain of the problems is the discrete set of feasible solutions or can be reduced to discrete.
 - ✓ The size of feasible solution set is countable: $\leq 2^{K}$
 - The goal is to find the best solution
 - ✓ To minimize the number of clusters and the degree of overlap

Conclusion

- Limitations of the design on the genetic algorithm
 - ☐ The search space of cluster centers is based on cluster head election
 - ➤ Not continuous.
 - There is little possibility that the result is the global optima.
- Future work
 - ☐ Develop the grid-based clustering method using genetic algorithm.
 - The search space could be larger.



•	"E:\2020\loT Course\NodeClustering\venv\python\Scripts\python.exe" "E:/2020/loT Course/Advanced-Software-Analysis-202102/SourceCode/mutation_check.py"
•	======================================
•	average # of generation: 521.7
•	average opt fitness: -3764.05
•	average time cost: 174.925
•	====================================
•	average # of generation: 531.1
•	average opt fitness: -3769.6
•	average time cost: 174.29375
•	======================================
•	average # of generation: 512.1
•	average opt fitness: -3794.35
•	average time cost: 157.1421875
•	mutation_prob=0.30000000000004
•	average # of generation: 509
•	average opt fitness: -3794.05
•	average time cost: 152.21953125
•	mutation_prob=0.4
•	average # of generation: 548.7
•	average opt fitness: -3783.8
•	average time cost: 162.134375
•	mutation_prob=0.5=
•	average # of generation: 523.75

average opt fitness: -3779.15average time cost: 134.6125

	alpha-0.0
average # of generation: 779.25	
average opt fitness: -4197.65	
average time cost: 421.65	
	alpha=0.2=
average # of generation: 579.05	
average opt fitness: -3794.75	
average time cost: 197.25859375	
	alpha=0.4
average # of generation: 554.4	
average opt fitness: -3789.2	
average time cost: 168.8671875	
	alpha=0.600000000000001
average # of generation: 534.75	
average opt fitness: -3794.15	
average time cost: 155.5921875	
	alpha=0.8
average # of generation: 537.35	
average opt fitness: -3798.8	
average time cost: 152.4421875	
	alpha=1.0
average # of generation: 540.35	
average opt fitness: -3783.95	

average time cost: 152.58046875

❖To see the impact of parent selection operators (max_interval = 500)
□No significant difference

	Result (running 20 times for the same initial pop)		
Operators	average # of generation	average opt fitness	average time cost (second)
Tournament selection	952.15	-3793.3	421.55
exponential ranking & roulette wheel sampling	947.85	-3808.75	393.19