Dynamic Clustering Methods for MANETs

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Clustering: General Motivation

- Enhance scalability, robustness
- Reduce communication information
- Favor spatial reuse
- Minimize control information
- Inter-cluster communication allow the creation of backbone-based architectures ("virtual architectures," "private networks," etc.)
- Improve the performance of the network

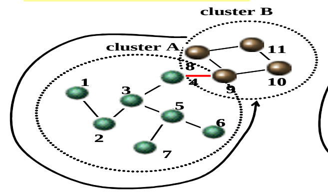
Novel Approach

- Most of the Existing Clustering Algorithms for Ad Hoc Networks aim on the construction of hierarchy without taking into consideration the various aspects of the network environment – Instead of helping the network, they may harm it because of the clustering overhead
- Our work on cluster generation differs from the existing ones on the fact that the network characteristics are taken into consideration *a priori* from the clustering methods. Those methods along with the appropriate metrics or combination of metrics can generate clusters that have the ability to boost the various performance aspects of the network.

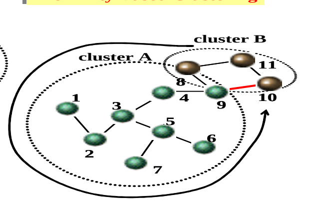
Motivation Example: Proximity vs. Mobility

If we do not Cluster based on the Mobility Characteristics of the nodes, the ReClustering Overhead will Harm the Network Performance

Mobility Based Clustering

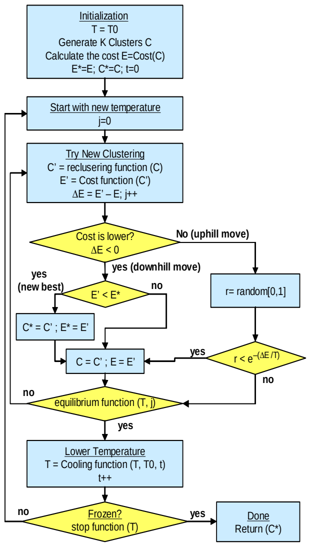


Proximity Based Clustering



: mobile nodes relatively static (same speed, same direction)
: static nodes (sensor nodes)

Simulated Annealing Algorithm For Clustering



Inputs	Examples
Equilibrium function	Constant (j = 5000); "Stop repeats" (function of
Cost function	$\sum_{i-1}^{K} Diameter\ (C_i)$
Cooling function	Geometric or logarithmic
Stop function	Minimum temperature (e.g., T=0.1); "Stop repeat" criteria
Reclustering function	Random move of one node
T0	Initial Temperature
K	Number of clusters

Variable	Definition
T	Current Temperature
C	Current Cluser map (e.g., {1,2},{3,6},{4,5})
C'	New cluser map to test (eg. {1,2},{3,5,6},{4})
C*	Champion cluster map (eg. {1,6},{3,5},{2,4})
E	Current cost
E'	Cost of new cluster map
E*	Champion cost
j	Inner loop counter
t	Outer loop counter

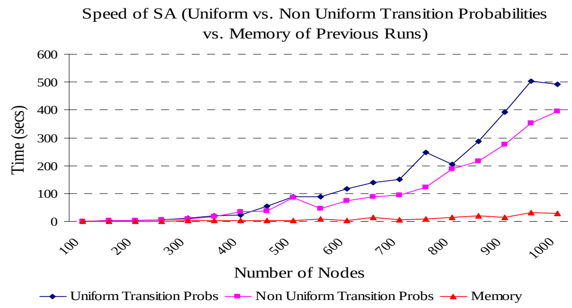
Metrics / Cost Functions

Description	Cost Function	Metrics Required
Balanced Cluster Size	$E = \min \sum_{i-1}^{K} N(C_i)^2$ $E = \min\left(Var\left(N^2(C_1), N^2(C_2),\ldots, N^2(C_K)\right)\right)$	$N(C_i)$: Number of Nodes in cluster C_i
Balanced Cluster Diameter	$E = Var\left(D_{C_1}^2,\ldots,D_{C_K}^2\right)$	D_{C_i} : Diameter (hops) in cluster C_i
Optimal Cluster Size	$E = \min\left(\sum_{i-1}^{K} N(C_i)^2 + \sum_{i-1}^{K}\left(N(C_i) - OptSize\right)^4\right)$	$OptSize$: Optimal Number of Nodes per Cluster
Number of Border Routers	$E = \min\left(\begin{matrix} Var\left(N^2(C_1), N^2(C_2),\ldots, N^2(C_K)\right) + \\ \left(\sum_{i-1}^{K} B(C_i)\right)\end{matrix}\right)$	$B(C_i)$: Number of Border Routers in Cluster C_i
Relative Direction	$E = \min\left[\sum_{z=1}^{K}\left(\sum_{i,j=1}^{\lvert C_z\rvert}\theta_{r_{i,j}}\right)^2\right]$ (1)	θ_i: Direction of node *i* $\theta_{r_{i,j}}$: Relative Direction of nodes *i, j* $\theta_{r_{i,j}} = \min\left(\lvert\theta_i - \theta_j\rvert, 360 - \lvert\theta_i - \theta_j\rvert\right)$,
Relative Velocity	$E = \min\left(\sum_{z=1}^{K}\left[\sum_{i,j=1}^{\lvert C_z\rvert} U_{r_{i,j}^z}^2\right]^2\right)$ (2)	$U_{r_{i,j}} = \sqrt{U_{x_{i,j}}^2 + U_{y_{i,j}}^2}$ $U_{x_{i,j}} = \lvert U\rvert\cos\theta_i - \lvert U\rvert\cos\theta_j$ $U_{y_{i,j}} = \lvert U\rvert\sin\theta_i - \lvert U\rvert\sin\theta_j$

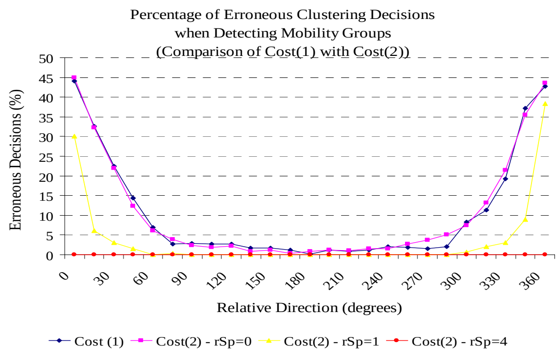
Optimizations to Improve SA Speed

- SA Annealing: Optimal Clustering Decisions but Slow
- Adjust State Transition Probabilities (Non-Uniform)
- Subsequent Runs of SA start from the Previous Clustering Decision (Memory)

Speed of Simulated Annealing



Clustering Efficiency



Conclusions

- Novel Approach: Takes Into Consideration the Network Dynamics
- The Modified SA Annealing Produces Good Clustering Decisions Much Faster so it can be Applied in a Dynamic Environment
- The Cost Functions Result in Very Efficient Clustering Decisions (Satisfy our Objectives)