The background is a dark blue gradient. On the left, there are two overlapping geometric shapes: a blue parallelogram and a light green parallelogram. Below these, there is a circular inset showing a detailed, high-contrast image of a circuit board. In the top right corner, there is a faint, stylized pattern of interconnected lines and squares, resembling a circuit or a data network.

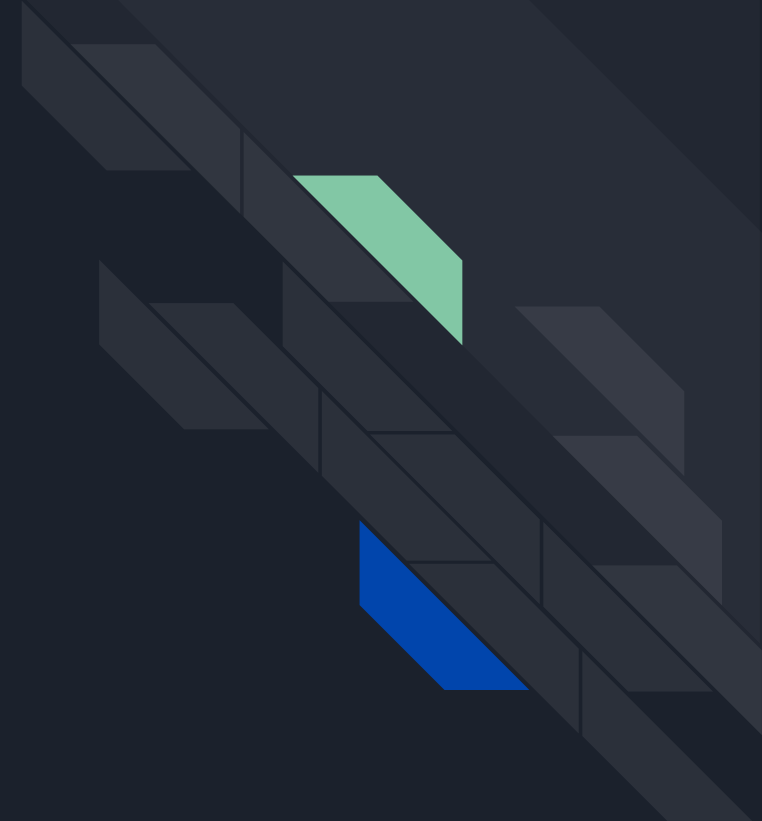
# A Distributed Group Mobility Adaptive Clustering

# Terminologies

MANET : Mobile Ad Hoc Network

Clusterhead

DGMA : Distributed Group Mobility Adaptive





# Objective

To convert a flat network to hierarchical network

In p2p network, when number of nodes becomes large, flat networks present problem in terms of storage and routing.

Length of routing table is proportional to number of nodes in network

Storage space per node is proportional to length of routing table

As storage space increases, interchanging routing info among nodes becomes more costly.



# Simulation Models

- Random Models
    - Random Walk
    - **Random Waypoint**
    - Truncated LevyWalk
  - Group Mobility Models
    - Nomadic Community Group Model
    - Pursue Group Model
    - **Reference Point Group Mobility**
    - Reference Velocity Group Mobility
    - Reference Region Group Mobility
- 



# DGMA Specifications

- 01 Mobility metric based on physical location. Macro movements are considered as part of mobility metric. Micro movements like intra-group movements are ignored.
- 02 Distributed nature : executed at each node only with local information
- 03 Adaptive to group partitions
- 04 A metric for measuring stability of cluster is used : Linear Distance based Spatial Dependency (LDSD) as metric for clustering



# Expected property of clusterheads ?

- 01 Prolonged lifetime of cluster
- 02 Adaptable to fast speed scenarios
- 03 Reduce frequency of re-clustering iterations



# LDTSD (Linear Distance based Total Spatial Dependency)

1. Exchange speed<sub>i</sub> and direction<sub>i</sub> with neighbours
2.  $RD(i,j) = \cos(\text{direction}_i - \text{direction}_j)$
3.  $SR(i,j) = \min(\text{speed}_i, \text{speed}_j) / \max(\text{speed}_i, \text{speed}_j)$
4.  $LDTSD(i) = RD^T SR$

RD is relative direction between node i and node j. For opposite direction, RD will be lowest and for same direction RD will be highest.

Similarly, SR represents the difference in speed of node i and node j in terms of ratio.

Higher LDTSD(i) implies more stability.



# DGMA Algo

T : duration of two nodes directly connected

n1 : ratio of white nodes in neighbourhood of red node

n2 : ratio of white node in neighbourhood of white node

Two main processes :

Nomination(input\_node): nominates the red clusterhead

Maintenance(input\_node): manages red, yellow and white nodes as algo progresses





# Disadvantages

Clustering stability is calculated in present terms (time) only. The LDTSD function is not concerned about future  $n$  steps or state of system at  $(t+1)$  step.

For example :

For node  $i$ , we have history of last positions

$(p(t-k), p(t-k+1) \dots p(t))$  for node  $i$

We have also history of movements of it's neighbours :

$(p(t-k), p(t-k+1) \dots p(t))$  for node  $j$



# Disadvantages ...

Available info :

$(p(t-k), p(t-k+1) \dots p(t))_i$  for node  $i$

And  $(p(t-k), p(t-k+1) \dots p(t))_j$  for all node  $j$  belonging to neighbour(node  $i$ )

To predict :

$\text{Pr}(\text{neighbourhood}_i) = \text{sum}(\log(\text{Pr}(\text{node } j)) \text{ for all node } j \text{ belonging to neighbour}(\text{node } i))$



## Disadvantages ...

2. Model only works properly on simulation models like RPGM or RRGm. Algorithm encounters a lot of change in cluster affiliations in case of Random models like Random Waypoint.