# Group Mobility and Partition Prediction in Wireless Ad-Hoc Networks

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***Abstract*–In wireless ad-hoc networks, network partitioning occurs when the mobile nodes move with diverse patterns and cause the network to separate into completely disconnected portions. Network partitioning is a wide-scale topology change that can cause sudden and severe disruptions to ongoing network routing and upper layer applications. Its occurrence can be attributed to the aggregate group motion exhibited in the movements of the mobile nodes. By exploiting the group mobility pattern, we can predict the future network partitioning, and thus minimize the amount of disruptions.**

**In this paper, we propose a new characterization of group mobility based on existing group mobility models, which provides parameters that are sufficient for network partition prediction. We then demonstrate how partition prediction can be made using the mobility model parameters, and illustrate the applicability of the prediction information. Furthermore, we use a simple but effective data clustering algorithm that, given the velocities of the mobile nodes in an ad-hoc network, it can accurately determine the mobility groups and estimate the characteristic parameters of each group.**

## I. Introduction

Wireless ad-hoc networks are networks dynamically formed by mobile hosts without the support of pre-existing fixed infrastructures. To provide communication throughout the network, the mobile hosts act as routers and cooperate to handle various network functions, such as traffic routing. The mobile hosts are moving with diverse mobility patterns that cause frequent failures and activations of the wireless links. Such frequent changes in the network topology pose significant challenges to the operations in wireless ad-hoc networks.

Researchers have proposed mobility prediction schemes [1] [2] that attempt to predict the future availability of wireless links based on individual node mobility model, in order to improve routing algorithm efficiency and build more stable routes. The changes in link availability are caused by *local* topology changes, however, *global scale* topology changes such as *network partitionings* cannot be predicted by these schemes. The main cause of network partitioning is the *group mobility behavior* of the mobile nodes in wireless ad-hoc networks, where the mobile nodes belonging to the same *movement group* exhibit similar movement characteristics, while the nodes of different groups show diverse mobility patterns. If we consider the scenario where the mobile nodes are initially dispersed and inter-mixed and many such *movement groups* exist, the distinct mobility pattern of each group causes them to separate, and network partitioning will eventually occur.

When a network partitions, the partitioned parts are completely disconnected from other parts of the original network. Upper layer routing and other applications involving nodes in separate partitions are severely disrupted, and may terminate if the partitions do not merge in time. Such situation is unacceptable in mission-critical network applications such as battlefield and rescue operations where every node must receive a certain level of Quality of Service (QoS) or have constant access to an important information depository. Therefore, to provision QoS guarantees for ad-hoc network applications, it is imperative to predict the occurrence of the network partitioning on a *global scale*.

In order to predict network partitioning, we need to identify and characterize the group-based movements of the mobile nodes, and use the characterization to quantitatively model the topology changes. Based on the topology changing pattern, we can then derive important information about future network partitionings. The main contributions of this paper are: First, we propose a new and enhanced characterization of the mobility groups based on existing models, which provides parameters sufficient for network partition prediction. Second, we show a method of predicting partition timing with the parameters provided by our enhanced group mobility model. Third, we use a simple data clustering algorithm such that, given the velocities of mobile nodes, it can accurately identify the mobility groups and estimate the characteristic parameters of each group necessary for the partition prediction. Finally, we illustrate that the clustering algorithm is effective with respect to mobility group identification.

The organization of this paper is as follows. Section II presents the existing group mobility model and our proposed extension. Section III describes the proposed partition prediction scheme and illustrates its applicability in a mission-critical service application. Section IV and V describes and illustrates the mobility-based clustering algorithm. Finally, Section VI concludes the paper.

## II. Group Mobility Model

In realistic ad-hoc network application scenarios such as conference seminar sessions, conventional events, and disaster relief operations, the mobile users are often involved in team activities and exhibit collaborative mobility behavior. Such user mobility can be modeled by a *group mobility model* where the mobile users are organized into groups of different mobility pattern, mobility rate, and coverage area. Researchers have previously proposed several group mobility models [3][4], for the purpose of simulating ad-hoc networks with group-based node movements.

### *A. Reference Point Group Mobility Model*

The *Reference Point Group Mobility* (RPGM) model was developed by Hong et al. in [4]. To represent the group mobility behavior of the mobile nodes, for each mobility group, the model defines a logical *reference center* whose movement is followed by all nodes in the group. The $(x, y)$ physical locations of the group's reference center and its node members are given by two levels of displacement vectors. The *group motion vector* maps out the location of the reference center, while the node-dependent *random motion vectors*, added to the group motion vector, give the positions of the nodes. The RPGM model describes the *group membership* of a mobile node by its physical displacement from the group reference center. For example, at time $t$, the location of the $i$th node in the $j$th group is given by the following:

- Reference location: $\mathbf{Y}_j(t)$
- Local displacement: $\mathbf{Z}_{j,i}(t)$
- Node location: $\mathbf{X}_{j,i}(t) = \mathbf{Y}_j(t) + \mathbf{Z}_{j,i}(t)$

The node-dependent local displacement or random motion vector, $\mathbf{Z}_{j,i}(t)$, gives the effect of the mobile nodes having their own localized movements while following the general group motion defined by the reference center.

The RPGM model can generate topologies of ad-hoc networks with group-based node mobility for simulation purposes, but for mobility or partition prediction purposes, it has two disadvantages. First, this model is used in the scope of an omniscient observer or a God, where the complete information about the mobility groups including their member nodes and movements are known. Given the distributed nature of the ad-hoc network, such global information about the mobility groups are not conveniently available to any mobile nodes at run-time. For example, a mobile user traveling to a destination does not know all the other users that are heading in the same direction. Therefore, the lack of prior knowledge about the mobility groups make the RPGM model inapplicable for run-time partition prediction. Second, the RPGM model represents the mobile nodes by their physical coordinates. Given only the instantaneous physical locations of the nodes, it is difficult to discern the nodes' group movement patterns and the trend in the network topology changes.

### B. Reference Velocity Group Mobility Model

We observe that instead of proximity in physical displacements, a more fundamental characteristic of a mobility group is the similarity of the member nodes' movements. The node movement can be characterized by the velocity $\mathbf{v} = (v_x, v_y)^T$, where $v_x$ and $v_y$ are the velocity components in the $x$ and $y$ directions. Therefore, we extend the RPGM model by proposing a velocity representation of the mobility groups and the mobile nodes: Each mobility group has a characteristic *group velocity*. The member nodes in the group have velocities close to the characteristic group velocity but deviate slightly from it. Hence, the characteristic group velocity is also the *mean group velocity*. The membership of the $i$th node in the $j$th group is then described as:

- Group velocity: $\mathbf{W}_j(t) \sim \mathbf{P}_{j,t}(w)$
- Local velocity deviation: $\mathbf{U}_{j,i}(t) \sim \mathbf{Q}_{j,t}(u)$
- Node velocity: $\mathbf{V}_{j,i}(t) = \mathbf{W}_j(t) + \mathbf{U}_{j,i}(t)$

We further extend the RPGM model by modeling the group velocity $\mathbf{W}_j(t)$ and the local velocity deviation of the member nodes $\mathbf{U}_{j,i}(t)$ as random variables each drawn from the distribution $\mathbf{P}_{j,t}(w)$ and $\mathbf{Q}_{j,t}(u)$, respectively. The distributions can be any arbitrary type, e.g. as Gaussian distributions, in order to model the various mobility patterns that may exist for different mobility groups and for the nodes within a mobility group.

Analogous to the RPGM model, the characteristic group velocity $\mathbf{W}_j(t)$ serves as a reference velocity for the nodes in the group. Therefore, we call this the *Reference Velocity Group Mobility* (RVGM) model. This velocity-based group representation is the time derivative of the displacement-based group representation in the RPGM model:

$$\mathbf{V}_{j,i}(t) = \frac{d\mathbf{X}_{j,i}(t)}{dt} = \frac{d\mathbf{Y}_j(t)}{dt} + \frac{d\mathbf{Z}_{j,i}(t)}{dt} = \mathbf{W}_j(t) + \mathbf{U}_{j,i}(t)$$

In particular, the characteristic group velocity $\mathbf{W}_j(t)$ is the changes over time in $\mathbf{Y}_j(t)$, the displacement of the group reference center. We can derive the reference point representation from the reference velocity representation, by integrating the velocities $\mathbf{W}_j(t)$, $\mathbf{U}_{j,i}(t)$, $\mathbf{V}_{j,i}(t)$ over an appropriate time interval, given the initial positions of the group reference center and the mobile nodes.

Our RVGM model has the following advantages. First, it directly provides the mobility parameters of each mobility group, such as its mean group velocity and the variance in the node velocities within the group. Second, by modeling the node velocities in a mobility group as a random variable with the distribution $\mathbf{Q}_{j,t}(u)$, we can determine the group membership of any mobile node given the nodal velocity and the velocity distributions of the existing mobility groups. In Section III, we will show how the mean group velocity and the mobile node's group membership information can be used to predict network partitioning in an ad-hoc network.

The velocity representation of our RVGM model also provides *a clearer characterization* of the mobility groups, as graphically illustrated in Figure 1[1] through the transformation of the mobile nodes from the a) physical to b) velocity data space.

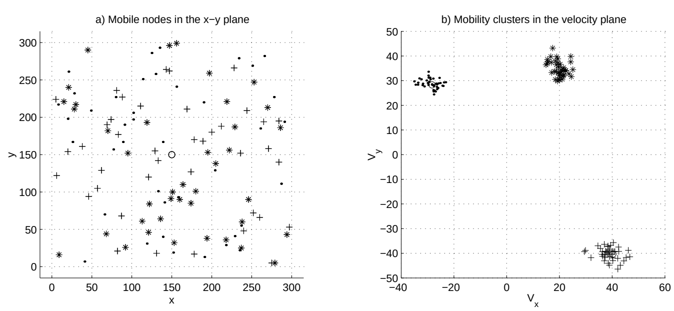


Fig. 1. Mobile Nodes Represented by Their a) Physical Coordinates and b) Velocities

In a) the reference centers of the groups overlap, and the mobile nodes are scattered with no clear groupings. However, in b) the mobile nodes are concentrated around the mean group velocity in their respective mobility groups and the mobility groups are clearly apparent. In Section IV, we will show how these properties of the mobile nodes in the velocity data space can be exploited to determine the mobility groups and the mobile node group memberships in an ad-hoc network.

## III. Partition Prediction

We first analyze how the group mobility pattern influences the changes in the ad-hoc network topology during a network parti-

[1] The *reference centers* and *group velocities* are shown by the symbol $\circ$, and the mobile nodes are marked with their mobility group symbols.

tioning. Figure 2 illustrates the progression of a network partitioning. The subplots (a), (b), (c), and (d) show the snapshots of the mobile nodes and the network topology at different times. At $t_0$=0, the mobile nodes are evenly dispersed in the coverage area, and the network is one large physical cluster. As the nodes move with the time, the physical cluster spreads in several directions at time $t_1$=4, and continues through $t_2$=8. By the time $t_3$=30, the original cluster is completely separated into three smaller "islands", and the network is partitioned.

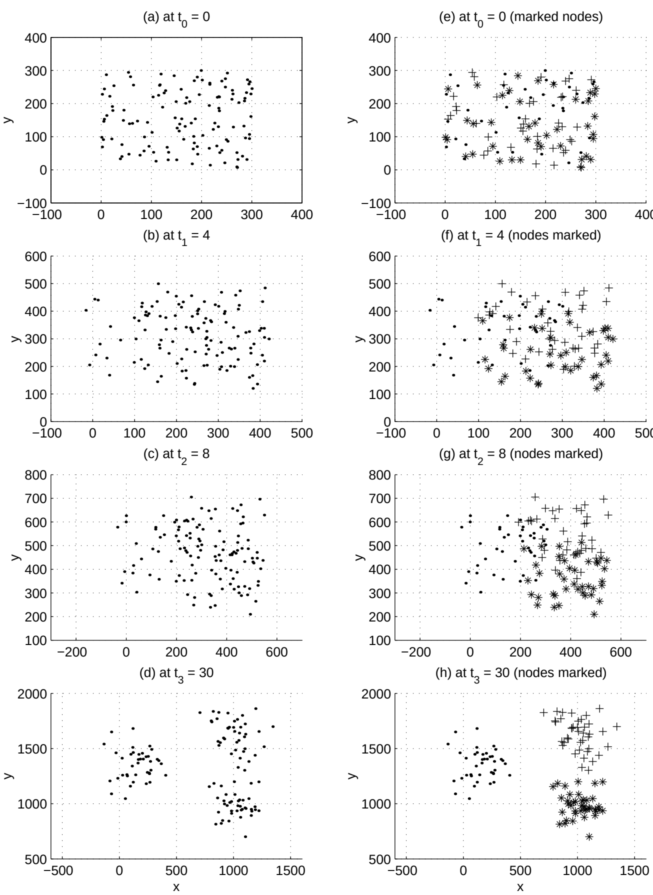


Fig. 2. Network Partition and Group Mobility Pattern

To observe the group mobility pattern in the network, suppose the group membership of the nodes are known. In subplots (e), (f), (g), and (h), we show the same set of topology snapshots but with the nodes marked by their respective mobility group symbols. The side-by-side comparison of the subplots clearly points to a cause-and-effect relationship between the group-based node movements and network partitioning. The mobility groups are moving at different velocities and towards different destinations, which causes the initially intermixed mobile nodes to separate and as the result, the network to partition. As expected, Figure 2(h) shows that the *sub-networks resulted from the network partitioning are the different mobility groups*.

### A. Partition Prediction Algorithm

From the above analysis, we observe that global scale changes in the network topology are attributed to the group mobility pattern. In particular, the movements of mobility groups lead to network partitioning. Consider again the ad-hoc network in Figure 2, where the underlying mobility groups have the same initial position and coverage area. The RVGM model characterizes each mobility group by its mean group velocity $\mathbf{W}_j(t)$. If such mean group velocities are known for all mobility groups in the network, then the occurrence of network partitioning due to the separation of mobility group can be predicted.

To simplify the problem, we make the following assumptions. First, we assume all mobility groups have a circular coverage area of diameter $D$ wherein the mobile nodes are uniformly distributed. Furthermore, we assume the velocities of the mobility groups and the mobile nodes are time-invariant, $W_j, V_{j,i} \neq f(t)$. Based on these assumptions, the network topology can be viewed as a collection of equal sized "circles" that are initially stacked on top of each other. We wish to calculate the time at which the "circles" completely uncover each other using the velocity of each "circle".

For example, a simple case of a network consisting of only two groups $C_j$ and $C_k$, each moving at the velocity $\mathbf{W}_j$ and $\mathbf{W}_k$. Since both groups are moving, to find the relative velocity between them, we fix one mobility group, e.g. $C_j$, as stationary. Then, the effective velocity $\mathbf{W}_{jk}$ at which $C_k$ is moving away from $C_j$ is:

$$\mathbf{W}_{jk} = \mathbf{W}_k + (-\mathbf{W}_j) \quad \text{and} \quad \mathbf{W}_{jk} = (w_{jk,x}, w_{jk,y})$$

where

$$\begin{aligned} w_{jk,x} &= w_{k,x} - w_{j,x}, \\ w_{jk,y} &= w_{k,y} - w_{j,y}. \end{aligned}$$

Initially, group $C_k$ completely overlaps with group $C_j$. In order for $C_k$ to fully separate from $C_j$, it must move past a minimum distance of the diameter $D$ of $C_j$'s coverage area. Hence, the amount of time for $C_j$ and $C_k$ to change from total overlap to complete separation is given by[2]:

$$T_{jk} = \frac{D}{\sqrt{w_{jk,x}^2 + w_{jk,y}^2}}$$

Consider an ad-hoc network consisting of many diverse mobility groups whose nodes are initially dispersed and inter-mixed. Given the mean group velocities, the time of separation $T_{jk}$ can be calculated for any pair of mobility groups. Therefore, *the occurrence of network partitioning can be predicted as a sequence of the expected time of separation $T_{jk}$s between the various pairs of mobility groups in the network*. E.g., an ad-hoc network with mobility groups $C_1$, $C_2$, and $C_3$, the network is predicted to partition at times $t$ = $T_{12}$, $T_{13}$, $T_{23}$.

### B. Application of Partition Prediction

Predicting *the occurrence* of network partitioning allows ad-hoc network applications to act in advance in order to minimize

[2] Since the coverage area of the mobility group is assumed to be a circle, which has equal diameter in every direction, hence, only the speed is sufficient to calculate the time of separation.

the disruptions caused by the partitioning. In addition, predicting *the timing* of the partitioning can further improve the efficiency and performance of the applications.

We illustrate with the example of a mission-critical service in ad-hoc networks. The service can be a critical information database or a web server that must be accessible to all mobile nodes in the network. The service runs on a single mobile node referred to as the server node, and instances of it can be dynamically replicated on any mobile nodes to guarantee service availability. Figure 3 illustrates how partition prediction information can ensure a high degree of service availability while minimizing the number of service replicas required. At time $t_0$, the server node $N_6$ is providing service $S$ to all mobile nodes in the network. However, at time $t_2$, the network partitions, as there are two mobility groups moving towards different directions. In order to continue the service in both partitions, service $S$ must be replicated onto the departing partition. In the figure, the server node $N_6$ executes the partition prediction algorithm and calculates the time of separation $T$ to be $t_2$. The server node $N_6$ timely replicates $S'$ onto $N_4$ at $t_1$ just before the partitions completely separate, and achieves service efficiency by not creating redundant replicates prior to that time.

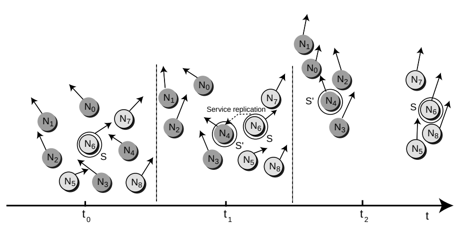


Fig. 3. Service Availability Guarantees with Partition Prediction

There is one additional important detail. The above service replication example implicitly assumes that node $N_6$ knows $N_4$ is in the separating partition. However, realistically, mobile nodes do not have the knowledge of which partition they will be in before the partitioning actually happens. The analysis earlier in this section shows, the network partitions are formed by the mobility groups. Therefore, *determining what partition a node will be in is equivalent to identifying the node's mobility group membership*.

Hence to make partition prediction, we need to determine both the mean group velocity of each mobility group and the group membership of each mobile node.

## IV. Mobile Node Velocity Clustering

In a wireless ad-hoc network, we do not have any prior knowledge about the mobility groups, the only information we may have is the velocities of all the mobile nodes, which we assume can be obtained via GPS. According to the RVGM model, the mobile node velocity in mobility group $j$ is represented as a random variable with the distribution $\mathbf{Q}_j$ and has the mean $\mathbf{W}_j$, which is the mean group velocity. Each mobility group is modeled as a velocity distribution. Figure 1 graphically illustrates the different velocity distributions as clusters in the velocity data space. *The centers of the clusters give the means of each velocity distribution, and the data points in each cluster are the mobile nodes with their mobility group membership revealed*.

Therefore, the problem of determining the mobility groups and the membership of mobile nodes becomes the identification of the mobility clusters in the velocity space: their centers and member data points, given only the velocity vectors of the mobile nodes.

### A. Sequential Clustering Algorithm

We propose to use a simple and effective *sequential clustering* (SC) algorithm from the field of pattern recognition [5] to solve this problem.

The SC algorithm classifies a set of data points into clusters based on a distance measure. It has three advantages that are suitable for our purpose. First, the algorithm requires little prior information about the data set; second, it learns about the clusters as it classifies and adapts its classification rules; and finally, it sequentially processes the data points, so the number of data points is not constrained and can be unknown. The last advantage is beneficial in wireless ad-hoc networks since the total number of nodes is dynamic and unknown.

The SC algorithm sequentially process each data point $x_i$ in three steps: (1) **Distance measurement**: it measures the Euclidean distance $d(x_i, C_k)$ between the data point and the center of each existing clustering $C_k$. The cluster center is the arithmetic mean of the velocity vectors of all member data points. (2) **Classification**: it selects the minimum distance measured and compares it with a pre-set distance threshold $\alpha$. If the minimum distance is less than $\alpha$, the data point is classified to the corresponding cluster. If there are not sufficient similarities between the data point and any of the existing clusters, then a new cluster is created with the data point as the first member. (3) **self-learning**: For each data point classified into an existing cluster, the algorithm self-learns about the cluster by updating the cluster center.

The SC algorithm has the structure as shown in Table IV-A:

TABLE I
SEQUENTIAL CLUSTERING ALGORITHM

| |
|---|
| $m = 1$ |
| $C_m = \{x_1\}$ |
| For $i = 2$ to end of data set |
|   Find $C_k$: $d(x_i, C_k) = \min_{1 \le j \le m} d(x_i, C_j)$ |
|   If $d(x_i, C_k) > \alpha$ AND $(m < m_{max})$ then |
|     $m = m + 1$ |
|     $C_m = \{x_i\}$ |
|   Else |
|     $C_k = C_k \cup \{x_i\}$ |
|     update the center of $C_k$ |
|   End |
| End |

Note that the SC algorithm boot-straps itself by classifying the first data point $x_i$ into the first cluster $C_i$. The additional parameter $m_{max}$ is the maximum number of clusters allowed, and it prevents too many clusters being created. The two parameters of the algorithm $\alpha$ and $m_{max}$ are set to some reasonably estimated values based on some prior knowledge about the mobility clusters/groups.

## V. Illustration of the SC Algorithm

We illustrate the performance of the Sequential Clustering (SC) algorithm using test data sets consists of a mixture of mobility groups. Each test data set has 150 data points generated from 3 Gaussian distributions of different mean and variance. The data points are input into the SC algorithm in a random order. We set the distance threshold $\alpha$ to a value that approximates the average difference between the means of the three Gaussian distributions. We also set $m_{max}$, the maximum number of clusters to 5.

In the first data set, Figure 4, the data points are generated from distributions of sufficiently different means, and hence form compact and well-separated clusters. The SC algorithm classifies all points correctly into three clusters, therefore correctly determines the mobility group membership of each node, and estimate the mean group velocities of all mobility groups with close to 100% accuracy.

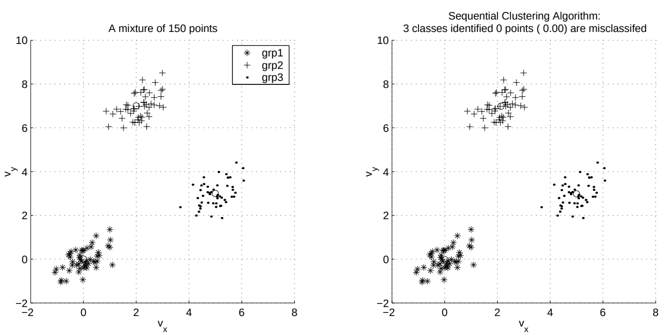


Fig. 4. Perfect Accuracy with No Misclassification

However, if the mobility groups have large amounts of scattering and closely placed mean velocities, the accuracy of the SC algorithm decreases. In Figure 5, the data points that extend into the areas of other clusters are misclassified[3]. The misclassification is due to the SC algorithm classifying into the same cluster all the data points that are within the Euclidean radius of $\alpha$. Because of the misclassified data points, the estimated centers of the cluster deviate from the actual centers, and hence reduce the accuracy of the estimated mean group velocities.

It is observed that as the mobility groups become less distinct and have larger overlaps, the number of misclassification of the SC algorithm increases. At the extreme, when there are little separations between the groups such that the distances between their mean velocities are less than the amount variance in each group, the SC algorithm will classify all data points into a single cluster. This is a correct classification, however, because if all mobility groups are sufficiently similar, they should be treated as one mobility group.

## VI. Conclusions and Future Work

In this paper, we proposed a velocity-based mobility group model that characterizes the movements of the mobility groups in

[3]The misclassified points are marked with the $\diamond$ symbol in the figures.

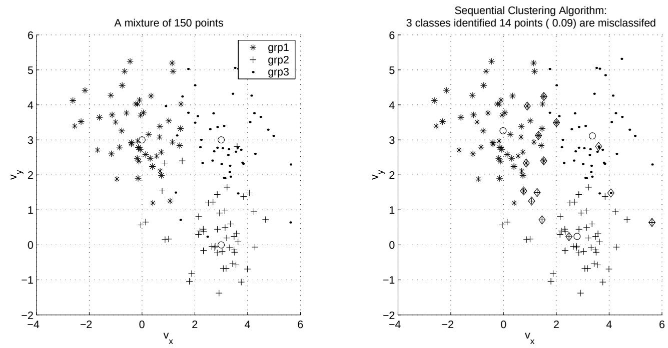


Fig. 5. Misclassification

wireless ad-hoc networks. Based on the mobility parameters provided by the model, we showed how future network partitioning can be predicted. We also proposed to use a low-complexity data clustering algorithm that can accurately determine the mobility groups and their mobility parameters, and identify the group membership of each mobile node in the network.

The main purposes of this paper were to show the cause-and-effect relationship between group mobility and network partitioning in the wireless ad-hoc networks, and investigate how mobility groups can be determined from node velocities. In this paper, we did not present any design or implementation details. In particular, we implicitly assumed the node velocities are known to the server which runs the data clustering algorithm. Realistically, a mechanism is required to efficiently collect the velocities from all mobile nodes. The mechanism should be scalable and does not incur high communication cost. One approach may be to piggyback the information on existing network communications. Additionally, the details of the partition prediction and subsequent service replication need to be developed. These will be the focus of our future research.

## VII. Acknowledgment

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