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Intermittently Connected Vehicle-to-Vehicle Networks: Detection and Analysis

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***Abstract*—Vehicular Adhoc Networks (VANETs) are dedicated to improve the safety and efficiency of transportation systems through vehicle to vehicle or vehicle to road side communications. VANETs exhibit dynamic topology and intermittent connectivity due to high vehicle mobility. These distinguished features declare a challenging question: how to detect on the fly vehicular networks such that we can explore mobility-assisted message dissemination and topology control in VANETs. As being closely related to network dynamics, vehicle mobility could be explored to uncover network structure. In this paper, we have observed that mobility of vehicle, rather than being random, shows *temporal locality* (i.e., frequently visiting several communities like home and office), and *spatial locality* (i.e., velocity constrained by road layout and nearby vehicles). We first examine temporal locality using a campus trace, then measure temporal locality similarity between two vehicles based on the relative entropy of their location preferences. By further incorporating spatial locality similarity, we introduce a new metric, namely *dual locality ratio* (DLR), which represents the mobility correlation of vehicles. Simulation results show that DLR can effectively identify dynamic vehicular network structures. We also demonstrate applications of DLR for improving performances of data forwarding and clustering in vehicle-to-vehicle networks.**

I. Introduction

Vehicular adhoc networks (VANETs) have recently received significant interest for improving road safety and drive convenience. For example, a vehicular network can propagate warnings to drivers behind a traffic accident to avoid multiple-vehicle collision. In another example, VANETs can prevent traffic jam by coordinating real-time traffic flow. As more and more vehicles are equipped with wireless communication devices, VANETs can be envisioned in foreseeable future.

Although being a subclass of mobile ad hoc networks (MANETs), VANETs have distinguished features from other ad hoc networks, such as wireless sensor networks (WSNs) and delay tolerant networks (DTNs). VANETs manifest *dynamic topology* and *intermittent connectivity* due to high mobility of vehicles. For instance, network structure changes in the way of vehicle groups birth (E), growth (A), combination (B), contraction (D), split (C), and death (F), illustrated in Fig. 1. That means that links frequently break or establish and network topology evolves dramatically over time. In addition, in Fig. 1(a), nodes in C (the green shadow) and F (the orange shadow) are disconnected from other nodes in the network because they are out of the transmission range of any node in A, B_1 and B_2, D, E_1 and E_2. In other words, when vehicle density is low, network has high probability of being disconnected. Such dynamic intermittent network connectivity hinders applications of mobility-assisted schemes for message dissemination and topology control in VANETs.

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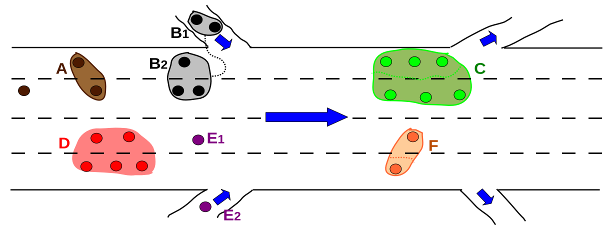
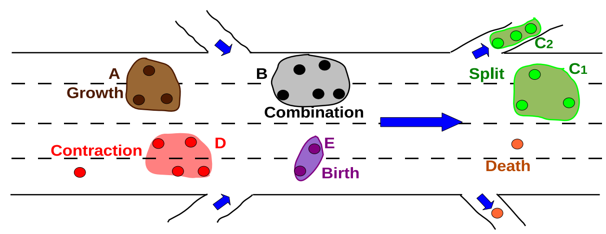


(a) $t = t_1$



(b) $t = t_2$

Fig. 1. Intermittent connected vehicle-to-vehicle networks.

The unique features of VANETs present a challenging question: *how to detect intermittently connected vehicle networks on the fly* such as to explore mobility-assisted data forwarding and topology control in VANETs. Since link dynamics and network structure evolutions are mostly determined by vehicle mobility, which is not a prior-knowledge, the challenge is *how to characterize mobility correlations among vehicles* such that we can trace real time network topology.

Fortunately, vehicle mobility is usually constrained by road layout, speed limit, traffic flow, and driver's destination rather than random. On one hand, car movement depends on the *close-by* vehicles (e.g., similar *speeds* and same moving *direction*) and geographic surroundings (e.g., road layout and speed limit), i.e., vehicle mobility reveals *spatial locality*. Vehicles with similar spatial locality properties can maintain stable links and move as a group for a long time. On the other hand, being driven by human, vehicles likely frequent several community sites, such as home and office, i.e., vehicle mobility, like human mobility [1], exhibits *temporal locality*. Vehicles with similar temporal locality properties have high chance to travel overlapping routes and meet one another. Thus, there is a close relationship between network structure and spatial-temporal locality similarity of vehicles.

Accordingly, we measure both spatial and temporal locality similarities for vehicle network detection. To begin with, *spatial* locality similarity between two vehicles is characterized by their relative distance, speed, and direction, which can be obtained by various localization methods [2], such as GPS. To quantify *temporal* locality similarity, we first investigate vehicle mobility based on a small-set of students trace with detailed information of locations and trajectories of driving activities. We have observed that vehicle mobility shows temporal locality, which is consistent with human mobility [1], [3]–[5]. Specifically, vehicular nodes mostly move on routes among few frequented places while occasionally make trips to other community sites, and such location preferences are changing over time. Next, we model the temporal locality using location profile, via relative entropy of which we quantify the temporal locality similarity. By considering both locality similarities, we derive a new metric, namely *dual locality ratio (DLR)*, for detecting VANETs topology and exploring DLR-assisted applications, such as data forwarding and clustering.

To validate DLR, we implement a *Time-Space varying Vehicular* (TSV) mobility model in OMNeT++ [6], which can reproduce the temporal and spatial locality features of vehicle mobility. Simulation results show that DLR can effectively detect intermittent connected vehicle networks. Furthermore, we explore applications of DLR in assisting message dissemination and topology control. By selecting nodes with low DLR as relays, delay tolerant message propagation has achieved much smaller delay than random forwarding. In mobility-aware clustering, by selecting the clusterhead with highest average DLR of nodes with their neighbors, cluster stability is considerably better than traditional clustering scheme, such as lowest-ID [7].

The rest of the paper is organized as follows. Section II first highlights the temporal locality of vehicle mobility by examining an empirical trace, then provides a locality modeling for quantifying temporal locality similarity. Section III presents a new metric, namely dual locality ratio (DLR), to measure mobility correlations among vehicles. In Section IV, simulation results, under time-space varying vehicular mobility model, show that DLR can detect dynamic VANETs topology. We apply DLR for assisting data forwarding and clustering in Section V, and finally conclude in VI.

II. Vehicle Mobility in Empirical Trace

In this section, we first examine a GPS trace file with detailed information of students driving activities to investigate how vehicle movements are dependent on time and location. Then, we model vehicle's time-varying location preference for quantifying mobility correlations among vehicles.

A. Temporal Locality in Vehicle Mobility

In order to properly interpret the moving behaviors of vehicles, we use a data set of students daily trace collected during a three-month period. The recorded trips include car trips and bus trips. Note that as the GPS receiver carried in a car requires a line of sight (LoS) from satellites, it cannot log short trips in a building complex area, which is a shortcoming for almost every trace file collected by GPS receiver. Since our trace has lots of detailed information of individually visited locations and driving paths, it is preferred over other large scale data sets, such as city wide transport system traces, which do not have such detailed information of each vehicle.

Fig. 2 illustrates an example of one day car moving trace of a student. From the figure, there are total 4 trips during that day. Upon the time sequence, the student visits four places: home → lab → class → church → home. This moving trace shows that a vehicle changes its movement path over time because the driver has different destinations at different time in order to execute various social activities. For instance, in the morning, the vehicular node moves on the roads from home to lab (trip 1); during the daytime, it moves around campus (trip 2); and in the evening, it travels from church back to home (trip 4). As its driver targets different places to execute different activities, a vehicle accordingly changes movement paths, i.e., vehicle's location preferences are time-varying.

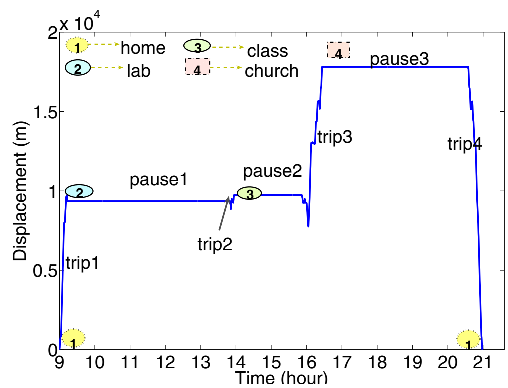


Fig. 2. An example of one day car moving traces.

In addition, the aggregated locations visited by students within one week, shown in Fig. 3, demonstrate that the majority community sites students daily visited are within 2-km-wide campus area. Vehicular nodes in this trace frequent several communities sites around campus and mostly move on roads among these places. In other words, vehicles frequently travel to preferred locations, i.e., vehicle mobility shows *temporal locality*.

More interestingly, given the collected GPS traces, we have found that there are many overlapping trajectories among car trips of students. That's probably because similar social duties and life schedules of students induce similar temporal locality. This observation reveals that vehicles with similar temporal locality likely meet and have potential to move as groups.

Remark 1: The vehicular mobility exhibits temporal locality, i.e., vehicles likely target several community sites with high

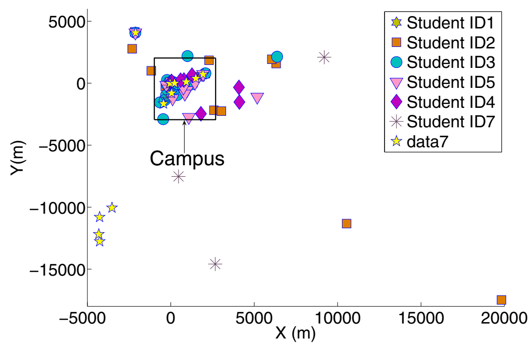


Fig. 3. Aggregated visiting locations of students.

preferences and such location preferences are time-varying. Similar temporal locality of vehicles, i.e., preference of adjacent locations, leads to overlapping moving paths and grouping phenomena.

B. Temporal Locality Modeling

In order to measure temporal locality similarity, we provide a *temporal locality modeling* based on above observations.

Given a network with M community sites, denoted as $\mathcal{M} = \{c_1, c_2, \cdots, c_M\}$. Community sites can be extracted from real map or partitions of network for simulation use. Since vehicular nodes visit different community sites (e.g., home, office, and grocery store) with different probabilities, we define a *location profile* as follows.

Definition 1: The real time location profile for n_i is $P_i(t) = \{p_i^{c_1}(t), p_i^{c_2}(t), \cdots, p_i^{c_M}(t)\}$, where $p_i^{c_m}(t)$ represents the probability that node n_i targets c_m at time t.

The location profile can be estimated based on historical movements of nodes. Studies on human mobility show that people tend to spend most of their time in few frequented communities [1]. For example, people usually drive to office every day and stay there for about 8 hours, while go to grocery store every week and stay there for about 1 hour. The probability that a mobile user visits location c_m is approximately proportional to the user sojourn time fraction of c_m. Thus, location profile can be estimated as

$$p_i^{c_m}(t) = \frac{\omega_i^{c_m}(t)}{\sum_{j=1}^{M} \omega_i^{c_j}(t)}, \tag{1}$$

where $\omega_i^{c_m}(t)$ is the average sojourn time of node n_i at community site c_m in n_i's daily movements history. Assume that vehicular nodes can record its location, either by GPS or other localization methods [2], like the campus trace we have used. By recording sequence of sites at which node n_i presents at each time interval, such as 10 minutes, $\omega_{c_m}^i(t)$ can be easily calculated. Hence, it is possible to obtain a vehicular node's location profile.

Remark 2: Definition 1 models the temporal locality as the time-varying location preferences of vehicle. The more similar location profiles, the more likely vehicles target same destination and have overlapping movement trajectories.

III. Dual Locality Ratio

In order to detect vehicular network topology, we measure the mobility correlations among vehicles, which include temporal and spatial locality similarities. Temporal locality similarity is induced by preferences of adjacent community sites, while spatial locality similarity is revealed by relative distance, speed, and direction. This section first quantifies both similarities separately, then by combining them, presents a new metric, namely *dual locality ratio (DLR)*.

A. Temporal Locality Similarity

In Section II, we have observed the temporal locality of vehicle mobility in real trace and modeled it by location profile, which specifies the probability of a vehicle visiting each community. Next, we take an *entropic* approach to measure the similarity between two location profiles.

In information theory, it is well known that the *relative entropy* $D(p||q)$ can measure the "distance" between two probability vectors p and q, which is defined as [8],

$$D(p||q) = \sum_{c_m \in \mathcal{M}} p(c_m) log \frac{p(c_m)}{q(c_m)}. \tag{2}$$

Eq. (2) gives a non-symmetric metric within $[0, \infty)$. By normalizing and symmetrizing Eq. (2), we define temporal locality similarity as follows.

Definition 2: Temporal locality similarity between vehicles n_i and n_j is

$$TLS_{i,j}(t) = 1 - \frac{D(P_i(t)||P_j(t)) + D(P_j(t)||P_i(t))}{2 \times \max\{D(p||q)\}}, \tag{3}$$

where $P_i(t)$ and $P_j(t)$ are location profiles of n_i and n_j at time t, respectively, and $\max\{D(p||q)\}$ is the maximum relative entropy of all vehicle pairs in a network.

Given Eq. (3), temporal locality similarity is symmetric to any node pair, and its range is mapped into $[0, 1]$. $TLS_{i,j}(t) = 1$ if and only if $D(P_i(t)||P_j(t)) = 0$ and $D(P_j(t)||P_i(t)) = 0$, i.e., two vehicular nodes have same location profile. Temporal locality similarity represents how likely they target same area or travel same routes. Vehicles with high temporal locality similarity are probably interested in traffic information of same roads, thus traffic jam warning can be disseminated only to interested cars rather than flooding the network.

B. Spatial Locality Similarity

Besides temporal locality, spatial locality properties, such as location, speed, and direction, also affect link dynamics and network connectivity. To proceed, let $d_{i,j}(t)$, $v_{i,j}(t)$, and $\theta_{i,j}(t)$ denote the Euclidean distance, relative velocity and moving direction between the node pair (n_i, n_j) at time t, respectively. Intuitively, two vehicles locating within small distance, moving with similar speeds and directions are more likely to maintain stable link. Hence, we define the *spatial locality similarity* of a node pair (n_i, n_j) as,

$$SLS_{i,j}(t) = \frac{1}{1 + ||d_{i,j}(t)||} \cdot \frac{1}{1 + ||v_{i,j}(t)||} \cdot \frac{1 + cos(\theta_{i,j}(t))}{2}. \tag{4}$$

Eq. (4) provides a simple measure of $SLS_{i,j}(t)$ with range $[0, 1]$. $SLS_{i,j}(t)$ increases when relative distance, speed, and moving direction decrease. When $d_{i,j}(t)$, $v_{i,j}(t)$, and $\theta_{i,j}(t)$ approach to 0, which means two nodes move together at same speed and direction, we have $SLS_{i,j}(t) \to 1$, implying the highest spatial locality similarity between nodes n_i and n_j. On the opposite, when the distance and the relative speed between these two nodes, $d_{i,j}(t)$ and $v_{i,j}(t)$, are large, or two cars move in opposite directions, $SLS_{i,j}(t)$ becomes very small, even approaches to 0. That means, there is very little or no spatial locality similarity between this pair of nodes.

C. Dual Locality Ratio (DLR)

By far, we have investigated temporal and spatial locality, both of which are essential in characterizing vehicle mobility. From mobility perspective, vehicles may mainly correlate in temporal locality, such as buses running the same route, or in spatial locality, e.g., cars on highway. From network performance perspective, contact-based properties, such as inter-meeting time and contact duration likely depend on temporal locality similarity, while link properties, such as link stability and lifetime, are mostly determined by spatial locality similarity between nodes. In order to characterize vehicle mobility correlation such as to adapt to different mobility scenarios as well as various network evaluations, we present a new *dual locality ratio* (DLR) metric by introducing a tune-up parameter α to jointly consider temporal locality similarity in Eq. (3) and spatial locality similarity in Eq. (4).

Definition 3: The **Dual Locality Ratio** (DLR) between two nodes n_i and n_j is given by

$$DLR_{i,j}(t) = \alpha TLS_{i,j}(t) + (1 - \alpha) SLS_{i,j}(t), \tag{5}$$

where $0 \leq \alpha \leq 1$ and $0 \leq DLR_{i,j}(t) \leq 1$.

The weights of temporal and spatial locality similarities can be adjusted through α. DLR degrades to spatial or temporal locality similarity by setting α as 0 or 1, respectively.

Remark 3: DLR measures mobility correlation between a pair of vehicles. The higher the DLR, the more likely two cars maintain a stable link and travel same route.

IV. Dynamic Vehicle Network Detection

Because the high vehicle mobility in VANETs, the network topology may change dramatically over time. For example, vehicle groups may be formed and re-grouped, or dismissed from time to time, as shown in Fig. 1. Here we study the application of DLR in detecting the dynamic network structures. First, we implement a *Time-Space varying Vehicular* (TSV) mobility model in OMNeT++, then use it to show simulation results regarding intermittently connected vehicle network detection and evolutions.

A. Time-Space Varying Vehicular Mobility Model

Assume M community sites and N nodes in the network. Locations of communities can be extracted from real map, or assigned by simulation input, or randomly delimited as partitions of network region.

To model the temporal locality of vehicle mobility observed from real trace, a node assigns time varying weights to each community site according to power law distribution to represent its frequent trips to a few locations and occasional visits to other places. An example with 5 communities in the network is shown in Fig. 4. Vehicle n_i at home location assigns probabilities $\{p_i^{c_m}(t), 1 \leq m \leq 5\}$ of choosing each location as next destination, i.e., location profile at time t. Using Eq. (1) reversely, the sojourn time n_i staying in community site c_m is obtained as $\omega_i^{c_m}(t) = p_i^{c_m}(t) * T$, where T is a constant (e.g., 1 day). Accordingly, node n_i spends most time at few frequented locations, while stays shortly at other places.

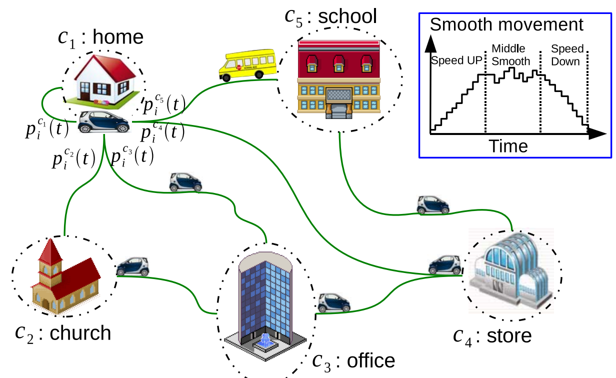


Fig. 4. TSV mobility: locality modeling and smooth movement.

More in details, each node selects one of the M communities as target with probability $p_i^{c_m}(t), 1 \leq i \leq N, 1 \leq m \leq M$, and randomly chooses a destination point around c_m. The node moves to its destination using smooth movement that first speeds up, then moves at stable speed, finally slows down before coming to a stop (see Fig. 4). The speed of smooth movement is proportional to the distance between starting point and the destination [9]. In other words, routes between different pairs of (c_i, c_j) have different smooth speeds, which mimics the spatial locality of vehicle mobility. When node n_i reaches its destination at c_m, it stays there for $\omega_i^{c_m}(t)$ period of time with small movements around c_m or short pauses. Then, node n_i repeats this process again. All N nodes in the network continue their movements until the end of simulation.

Before using time-space varying vehicle (TSV) mobility for VANETs detection, we run simulations to make sure that TSV mobility exhibits empirically observed truncated power-law decay of inter-contact time [10]. Simulation runs for 24 hours with 20 nodes moving in a 5-community network area as shown in Fig. 4. The transmission range is set as 250 meters. Fig. 5 shows the complementary CDF (CCDF) of the inter-contact time, i.e., $\mathcal{P}\{T_I > t\}$, on a log-log scale with simulation area ranging from $1000m \times 1000m$ to $5000m \times 5000m$. Consistent with the studies in [10], the inter-contact time follows a truncated power-law distribution and for the $5000m \times 5000m$ simulation area, the power-law behavior is dominant over up to $O(10^4)$ seconds, followed by a sharp decrease beyond that timescale.

Remark 4: TSV mobility model not only mimics temporal-spatial locality of vehicle mobility but also yields power law

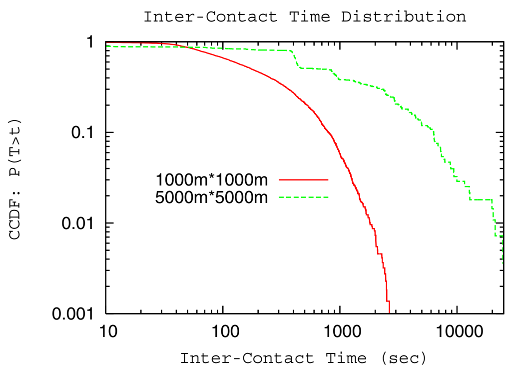


Fig. 5. Inter-contact time under TSV mobility.

and exponential decay dichotomy of inter-contact time. Therefore, we use TSV to evaluate dual locality ratio.

B. Intermittent Connected VANETs Detection

Vehicle networks are intermittently connected due to car movements and possible low node density. A number of vehicles are considered forming groups as being related in some way, such as within each other's transmission range and maintaining relative stable links. We define a vehicle group as follows.

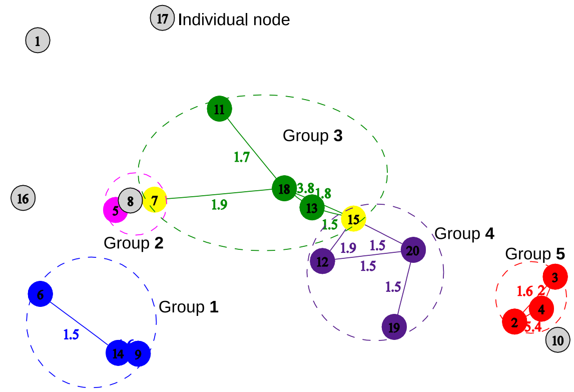
Definition 4: Let DLR_{th} be the required *grouping threshold* for vehicles to form a group. Two neighboring vehicles n_i and n_j are in the same group, if $DLR_{i,j}(t) \geq DLR_{th}$.

Using the same simulation setting as in Section IV-A, Figs. 6(a) and 6(b) show the group structures at time $t_1 = 1000$ sec and $t_2 = 1010$ sec, respectively. The group structures are identified using DLR by setting DLR_{th} as the average DLR of all pairs of nodes, which is 1.5 for Fig. 6.

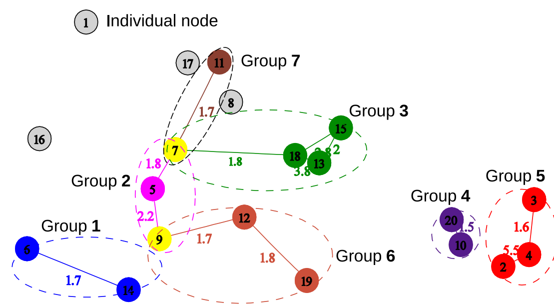
In Fig. 6, nodes with the same color belong to the same group; the yellow nodes, such as node 7, belong to two or more groups; and each gray node is in a group only containing itself. The number on an edge between two nodes is the DLR between them. For two nodes without connection, it means that the DLR between them is lower than threshold DLR_{th}.

We can see that DLR is able to detect meaningful group structures in intermittent VANETs. For example, in Fig. 6(a), although node 10 is close to nodes 2, 3, and 4, it is not a member of *Group 5*, which means that the DLR between node 10 and any node in *Group 5* is small. After $10s$, Fig. 6(b) shows that node 10 moves to a location that is further away from *Group 5*. Thus, node 10 should not be considered as a group member to *Group 5* as it has different path from this group. By comparing Fig. 6(a) and 6(b), the *Group 4* with nodes 12, 20, 15 and 19 dismisses after $10s$ because the DLRs among these nodes are relatively small. On the contrary, the DLRs between nodes 2 and 4, nodes 13 and 18 are relatively high, which means that the links between them are relatively stable and can exist for a relatively long period of time. Hence, DLR also presents a good measure of link and group stability.

Remark 5: Simulation results show that dual locality ratio can capture the dynamic group structures in VANETs. It also indicates the link and group stability, thus could be a useful metric for evaluating quality of network connectivity and predicting topology evolutions and network partition.



(a) Network structure at $t_1 = 1000$ sec.



(b) Network structure at $t_2 = 1010$ sec.

Fig. 6. Intermittent connected vehicle network detection.

V. Applications

Besides network topology detection, we explore applications of dual locality ratio in message dissemination and mobility-aware clustering.

A. DLR-Assisted Message Dissemination

As one of the goals of intelligent transportation system is to disseminate messages in a dynamic and intermittently connected network, we develop a DLR based data forwarding mechanism for delay tolerant information propagation in vehicle-to-vehicle networks.

Assume that neighboring nodes can exchange locality information, including location profile, current location, moving speed, and direction. Denote the neighbors set of data source S as $N_S = \{n_1, \ldots, n_k\}$. Assume that destination D is not in the set N_S, otherwise S can simply transmit the data to D immediately. Message propagates according to the following steps: i) S collects the location information of its neighbors by exchanging messages; ii) Using Eq. (5), S calculates the dual locality ratio $DLR_{S,i}$ between itself and its neighbor n_i, $\forall n_i \in N_S$; iii) S sends a copy of the message to relay R which has the *weakest* DLR with S, i.e., $DLR_{S,R} = \min\{DLR_{S,i}, n_i \in N_S\}$; iv) S, R repeat steps ii) and iii) every Δt period of time until at least one of the relay nodes transmits the message to D or the message expires.

In order to choose appropriate Δt, we resort to recent car driving experiments. Paper [11] showed that the median duration of WiFi connectivity at vehicular speed (around 60 km/hour) is 13 seconds. In other words, average contact duration of high speed vehicles is at seconds level. Hence, we set $\Delta t = 10$ seconds to enable message carrier establishing new neighborhood and finding new relay.

Using the same network setting as in Section IV-A, simulation results show that DLR-assisted data forwarding outperforms random forwarding, which randomly chooses a neighbor as relay every 10 seconds. The DLR-based message dissemination achieves about 20% decrease in end to end delay under RWP mobility, and about 60% decrease under TSV mobility by taking advantages of group structures. Because of page limit, the figure is not included.

Since DLR indicates the probability that two nodes move as a group, small DLR means different moving directions or paths. By distributing messages to vehicles with different movement behaviors, the chance that at least one of the relays meets destination D is increased, thus information can be propagated to destination within shorter time than randomly selecting relays. Hence, DLR is useful in assisting message dissemination in vehicle-to-vehicle network.

B. DLR-Assisted Clustering

We further utilize dual locality ratio in mobility-aware clustering, which is one of the most general applications of topology control, and show its benefit of lower clusterhead changing rate comparing with lowest-ID algorithm [7].

In lowest-ID clustering algorithm, each node is randomly assigned an ID, and the node with smallest ID among its neighbors acts as clusterhead. Because vehicles move at high speed and may travel different routes to their destinations, a node may be frequently disconnected with its randomly selected clusterhead, i.e., clusters based on lowest-ID are unstable. The stability of clusters could be improved by selecting clusterhead based on average DLR of nodes with their neighbors.

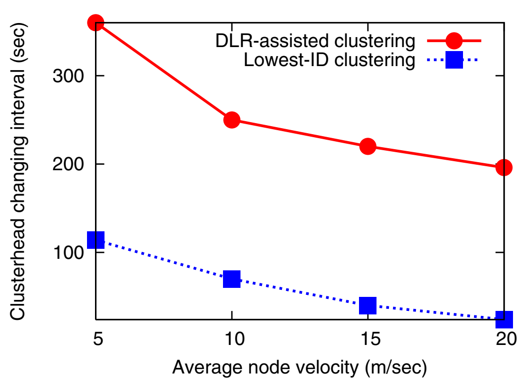


Fig. 7. DLR assists clustering under TSV mobility.

Using the same simulation setting as in Section IV-A, the average clusterhead changing time is measured to indicate cluster stability. Fig. 7 shows that under various vehicle speeds, changing interval of clusterhead selected base on DLR is much longer than that based on lowest-ID. A node with higher average DLR not only moves closely with its neighbors, but also may share overlapping paths, therefore is much less likely to be disconnected from its cluster members if being selected as the clusterhead, i.e., changing rate of clusterhead is reduced. Therefore, DLR can be used to obtain stable clustering for topology control of vehicle-to-vehicle network.

VI. Conclusion

In this paper, we have investigated detection of intermittent connected vehicle-to-vehicle networks in which vehicles are temporally as well as spatially related to each other. Using a GPS trace file, we highlight the temporal locality of vehicular mobility, and model it using location profile. Based on relative entropy, temporal locality similarity is quantified as the similarity between location profiles to represent association degree of vehicles' trajectories. By jointly considering temporal and spatial locality similarities, we propose *dual locality ratio* (DLR) metric to measure mobility correlation between a pair of nodes. Simulation results show that DLR can effectively identify dynamic vehicle groups. We further apply DLR to assist data forwarding and clustering, in which DLR improves end to end delay and clusterhead stability, respectively. Future work includes to explore more applications of DLR and to extend our approach to other forms of ad hoc networks.

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