Range-based Mobility Estimations in MANETs with Application to Link Availability Prediction

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***Abstract*— The quality of communications in mobile ad-hoc networks is largely determined by the topological stability. Characterizing the mobility of mobile nodes (e.g. how often they move away from each other) would enable the measurement of the frequency of network reconfigurations for predicting stability. In this paper, we first define a triplet $\langle V, \Theta, \Psi \rangle$ which consists of mobility parameters that are directly correlated with the stability of a network (e.g. inter-node relative speeds/orientations and epoch time). Based on our previous study on range-based velocity estimations, we then propose a new scheme to estimate the mobility parameters in realtime. In contrast to existing methods that are based on either localization systems or features of wireless channel, the proposed scheme estimates the parameters $\langle V, \Theta, \Psi \rangle$ only from the time-varying inter-node distance information while retaining its reliability and accuracy even in noisy environments. The performance of the proposed scheme is validated in computer simulations against an existing method under different network settings. We also apply the proposed scheme to link availability estimation as a more lightweight way of obtaining mobility parameters using an existing tool. Preliminary results for various scenarios show that, with the proposed scheme, the tool achieved a comparable performance to when *a priori* knowledge of nodal mobility is used.**

***Index Terms*— Mobility, Link duration, Link availability, Epoch time, GPS-free, MANET**

I. Introduction

A typical mobile ad-hoc network is a collection of wandering mobile nodes which form infrastructureless networks from temporary wireless links. The quality of communications in mobile ad-hoc networks suffers from frequent topological changes caused by the relative movements between mobile nodes. Accurate and reliable approximation of nodal mobility (e.g. relative speeds and orientations between mobile nodes and their average epoch time[1]) in realtime is necessary for predicting the stability of the network topology for different configurations/mobility models. For example, knowledge of the relative velocity between mobiles nodes and the average epoch time is useful in predicting link availability [2] and provisioning of adaptability for routing schemes [3].

Conventionally, the mobility of a mobile node, i.e. its velocity and epoch time, can be inferred from its changing positions [4] with the help of a localization system, such as the Global Positioning System (GPS) or a GPS-free positioning system [5]. However, the GPS signal is normally too weak to be of any use indoors. The GPS-free positioning systems [5] [6] may be used as alternatives to GPS. But such localization systems require the presence of stable anchor nodes, which may not exist in ad-hoc networks where every node is moving constantly. In addition, these systems are too complex and computationally expensive just for tracking nodal mobility.

Some techniques specialized in velocity estimations make use of characteristics of the wireless channel and/or received signal. For example, Doppler frequency is utilized in [7] [8] [9] for mobile velocity estimation. The first moment of the instantaneous frequency of the received signal is used in [10] to yield better performance. But these techniques have a common problem, i.e. they rely on precise knowledge of the properties of specific wireless channels or received signal. This limits their applicability to only scenarios where the pattern of signal propagation is constant.

The relative movements between nodes cause the inter-node distance to change over time. In a recent study [11] a Link Prediction Algorithm (LPA) is presented to predict link breakage by utilizing the time-varying inter-node range information, instead of the properties of wireless channel, for velocity estimations. However, this method assumes the measured range information to be noise-free [11], which makes it not feasible in normal noisy communication environments.

In previous work [12], we studied Range-based relative Velocity Estimations (RVE) for mobile ad-hoc networks. Using barely the information of the inter-node distance measured in realtime by techniques such as Time-of-Arrival (ToA) [13], the RVE estimators are less dependent on signal characteristics and are more robust in noisy scenarios. In this paper, we first define a triplet $\langle V, \Theta, \Psi \rangle$ to represent mobility parameters (e.g. the inter-node relative speed/orientation and the epoch time) that are directly correlated with the topological stability, i.e. link availability [1] [2]. Based on our work on the RVE estimators, we then propose a new scheme of mobility estimations, which allows mobile nodes to derive $\langle V, \Theta, \Psi \rangle$ in realtime. The performance of the proposed scheme is validated by computer simulations in networks of different properties. We also apply the proposed scheme to a tool for link availability estimation [2] as a more lightweight way of obtaining mobility parameters. Preliminary results show that,

[1]As defined in [1], an epoch is a segment of a mobile node's path, during which the node travels in a constant direction at a constant speed. The time a node spent on one epoch is defined as the epoch time.

with the proposed scheme, the performance of the tool for networks of different mobility models (e.g. Random WayPoint and Random Walk [14]) is comparable to when the nodal mobility is assumed to be known *a priori*.

The organization of this paper is as follows. In Section II, we present the new scheme of mobility estimations including the methods for estimating the relative speed and orientation as well as epoch times. The simulation model used for performance evaluation of the scheme and the results are introduced in Section III. In Section IV, we demonstrate how the proposed scheme is applied to link availability predictions and then discuss the preliminary results. Finally, we conclude the paper in Section V.

II. The Scheme of Range-based Mobility Estimations

In this section, we introduce the proposed scheme of mobility estimations based on the RVE estimations (e.g. *RVEd*) presented in [12]. In a mobile ad-hoc network of $\mathcal{N}$ nodes, we assume that each node periodically measures the distances to its one-hop neighbors by means of either received signal strength (RSSI), time-of-arrival (ToA) or time-difference-of-arrival (TDoA) measurements. Without taking the effect of Non-Line-of-Sight (NLOS) conditions into account, a distance estimate produced by any of these methods at time *i*, $\hat{d}_i$ can be simply modeled as:

$$\hat{d}_i = d_i + \epsilon_i \quad (1)$$

where d_i is the true value of the distance and ϵ_i is the measurement noise that can be modeled as a zero-mean Gaussian random variable with variance σ_ϵ^2. Every node also reports its collection of distance estimates to all of its one-hop neighbors. Thus, every node knows not only the distances to its one-hop neighbors but also those between its neighboring nodes within the one-hop neighborhood. The measurements and exchanges of distance information are carried out at a frequency of $1/\Delta t$, which can be finely tuned according to the resolution requirement of the mobility estimation.

Let $\mathcal{R}_i$ be the set of node *i*'s one-hop neighbors that are also one-hop away to each other. In the proposed scheme, we define $\langle V_i, \Theta_i, \Psi_i \rangle$ as a triplet of mobility parameters for a node *i*, where $V_i = \{\hat{v}_{ik} | k \in \mathcal{R}_i\}$ and $\Theta_i = \{\hat{\theta}_{ik} | k \in \mathcal{R}_i\}$ are the sets of estimated *i*'s speeds and orientations relative to its one-hop neighbors, respectively. $\Psi_i = \{\psi_n | n = 1, 2, ..., \mathcal{C}\}$ is the collection of $\mathcal{C}$ past epoch time of node *i*.

A. Estimating inter-node Relative Speeds and Orientations

As shown in Fig.1, given the presence of at least two neighbors within the radio coverage ($(j,k) \in \mathcal{R}_i$) including a *departing node* (the definition and speed estimation of a *departing node* is given in the Appendix), i.e. node *j*, a node *i* can derive $\hat{v}_{ik}$ and $\hat{\theta}_{ik}$ in realtime using the *RVEd* method as described below.

The relative positions and distances among the three nodes *i*, *j* and *k* are changing over time due to their relative movements. The changes in the distances among these nodes also cause their included angles to vary over time. As these nodes periodically exchange with each other the distance information to their one-hop neighbors, node *i* is able to calculate these time-varying included angles at every time slot (e.g. Δt). Let $\mathcal{I}_0$ be the distance between node *j* and *k* measured at time $t - \Delta t$. Let $\mathcal{K}_0$ and $\mathcal{J}_0$ be node *i*'s distance to *j* and *k* measured at the same time, respectively. According to the *Cosine Rule*, the included angle of $\mathcal{K}_0$ and $\mathcal{J}_0$, φ_i, is given by:

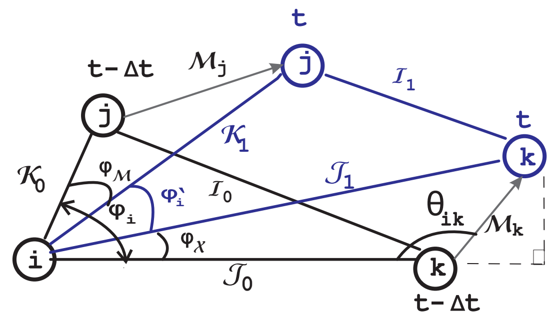

Fig. 1. the changes in the ranges and the orientations between node *i*, *j* and *k* caused by their relative movements during time slot Δt

$$\varphi_i = cos^{-1} \frac{\mathcal{K}_0^2 + \mathcal{J}_0^2 - \mathcal{I}_0^2}{2\mathcal{K}_0\mathcal{J}_0} \quad (2)$$

Similarly, given the distance estimates among *i*, *j* and *k* sampled at time *t* (e.g. $\mathcal{I}_1$, $\mathcal{K}_1$ and $\mathcal{J}_1$), the included angle $\varphi_i^{'}$ can be calculated by:

$$\varphi_i^{'} = cos^{-1} \frac{\mathcal{K}_1^2 + \mathcal{J}_1^2 - \mathcal{I}_1^2}{2\mathcal{K}_1\mathcal{J}_1} \quad (3)$$

The change of the angle φ_i to $\varphi_i^{'}$ from time $t - \Delta t$ to *t* is the result of both node *j*'s and *k*'s movements relative to *i* during Δt. Assuming that during Δt *j* and *k* does not cross each other[2], there could at most be 4 possible relative movement patterns among node *i*, *j* and *k* in the time slot (see Fig.2). Let $\varphi_\mathcal{M}$ be the included angle of $\mathcal{K}_0$ and $\mathcal{K}_1$ and $\varphi_\mathcal{X}$ be the included angle of $\mathcal{J}_0$ and $\mathcal{J}_1$. The various relative movement patterns demonstrated in Fig.2 result in 4 different relationships between φ_i, $\varphi_i^{'}$, $\varphi_\mathcal{M}$ and $\varphi_\mathcal{X}$, which can be summarized in Eq.4 as:

$$\varphi_\mathcal{X} = \begin{cases} |\varphi_i - \varphi_i^{'} - \varphi_\mathcal{M}| & \varphi_i \geq \varphi_i^{''} \\ |\varphi_i - \varphi_i^{'} + \varphi_\mathcal{M}| & \varphi_i < \varphi_i^{''} \end{cases} \quad (4)$$

where $\varphi_i^{''}$ is the included angle of $\mathcal{J}_0$ and $\mathcal{K}_1$. From Eq.4, we could obtain the value of $\varphi_\mathcal{X}$ for deriving node *k*'s velocity relative to *i* during Δt if $\varphi_\mathcal{M}$ and $\varphi_i^{''}$ is known. As node *j* is a *departing node* and the relative speed of *j*, $\hat{v}_{ij}$, is known (see Appendix), we can calculate $\varphi_\mathcal{M}$ ($\varphi_\mathcal{M} \geq 0$) by:

$$\varphi_\mathcal{M} = cos^{-1} \frac{\mathcal{K}_0^2 + \mathcal{K}_1^2 - \mathcal{M}_j^2}{2\mathcal{K}_0\mathcal{K}_1} \quad (5)$$

where $\mathcal{M}_j$ ($\mathcal{M}_j = \hat{v}_{ij}\Delta t$) is the distance that node *j* moved during Δt relative to *i*. However, it is very difficult to calculate

[2]The cases when node *j* and *k* cross each other is not discussed, as they rarely happen if the time slot Δt is short (e.g. 1 second). Even if the two nodes do cross each other on some occasions, they can be detected and treated as exceptions.

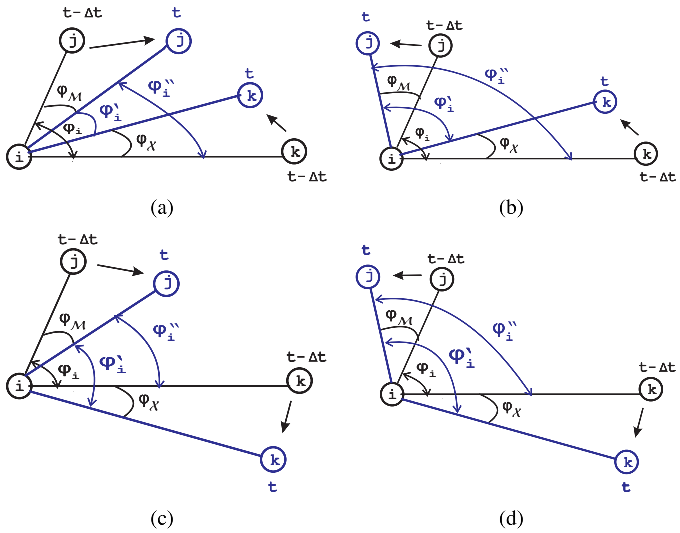

Fig. 2. Four possible movement patterns of node *j* and *k* relative to *i* during time slot Δt.

```
Velocity_Change_Count = 0 ;

for n in Neighbor_Set R

    Curr_Vn = Estimate_Relative_Speed ( n ) ;
    Curr_θn = Estimate_Moving_Orientation ( n ) ;

    if ( Prev_Vn != Curr_Vn || Prev_θn != Curr_θn )
            Velocity_Change_Count++;
            Prev_Vn = Curr_Vn ;
            Prev_θn = Curr_θn ;
    end if

end for

if ( Velocity_Change_Count == Number_of_Neighbors_in_R )

    Epoch_Times [i++] = Current_Time – Last_Epoch_Time;
    Last_Epoch_Time = Current_Time ;

else Curr_Epoch_Elapsed = Current_Time – Last_Epoch_Time;

end if
```

Fig. 3. Pseudo Code for Estimations of Epoch Times

$\varphi_i^{''}$ as its opposite side connecting *k* at time $t - \Delta t$ and *j* at time *t* is not measurable. Without knowing $\varphi_i^{''}$, we will have two values of $\varphi_{\mathcal{X}}$ from Eq.4 with one of them being the true value. The true $\varphi_{\mathcal{X}}$ can be identified from two sets of values of $\varphi_{\mathcal{X}}$. One can produce the second set by using the same method with another velocity-known node or with node *j* at Δt time later[3]. Let $\varphi_{\mathcal{X}}^A(\varphi_0^a, \varphi_1^a)$ and $\varphi_{\mathcal{X}}^B(\varphi_0^b, \varphi_1^b)$ be the two sets of values produced by the *RVEd* method with two velocity-known nodes or two time slots. We can determine the true value of $\varphi_{\mathcal{X}}$ by:

$$\varphi_{\mathcal{X}} = \varphi_{\mathcal{X}}^A \bigcap \varphi_{\mathcal{X}}^B \tag{6}$$

Therefore, we can estimate *k*'s speed relative to node *i* during time slot Δt, $\hat{v}_{ik}$ by:

$$\hat{v}_{ik} = \frac{\mathcal{M}_k}{\Delta t} = \frac{\sqrt{(\mathcal{J}_1 cos\varphi_{\mathcal{X}} - \mathcal{J}_0)^2 + (\mathcal{J}_1 sin\varphi_{\mathcal{X}})^2}}{\Delta t} \tag{7}$$

and the relative orientation $\hat{\theta}_{ik}$ by:

$$\hat{\theta}_{ik} = cos^{-1}\frac{\mathcal{J}_0^2 + \mathcal{M}_k^2 - \mathcal{J}_1^2}{2\mathcal{J}_0\mathcal{M}_k} \tag{8}$$

B. Estimating Epoch Time

The epoch time ψ_n of node *i* ($\psi_n \in \Psi_i$) can be determined by recording the time when the node starts a new epoch (or finishes the last epoch). Without the help of any localization systems or any speed meters, a node can not detect the changes in its own moving speed or orientation. Nevertheless, provided the presence of 2 or more neighbors most of the time, a node can still detect the start/end point of an epoch according to the fact that the changes in its moving direction/speed affect its relative speeds/orientations to all of its neighbors. The pseudo code for the implementation of the algorithm for estimating epoch time in a node is listed in Fig.3.

[3]Supposing that node *k* does not change its velocity during the past $2\Delta t$ time.

In the implementation, node *i* initializes a counter with value 0 at the beginning of updating sets V_i and Θ_i. The value of the counter is increased by 1 if a change in the speed or orientation to a neighbor in set $\mathcal{R}_i$ is detected. After this round of relative speed and orientation updates, current time is recorded as a starting point of a new epoch if the value of the counter equals $|\mathcal{R}_i|$, i.e. the number of node *i*'s one-hop neighbors whose velocities have been estimated using the *RVEd* method. Therefore, epoch time is obtained from intervals between the starting points of consecutive epochs. Elapsed time of the current epoch is also recorded. The use of this information for link availability estimation is given in Section IV.

III. Performance Evaluation of the Scheme of Mobility Estimations

To validate the performance of the proposed scheme of mobility estimations, we deploy the ns-2 simulator to simulate various network scenarios of different speed limits and mobility models in two experiments.

A. Simulation Model

The simulated mobile ad-hoc network consists of $\mathcal{N} = 40$ nodes moving around in a square area with the size of $\mathcal{L} \times \mathcal{L}$. The radio radius *r* of a node is fixed at 250m. Using both of the mobility modelling tools described in [15] and [16], the simulations cover a wide range of nodal mobility characterized by the Random Waypoint Model [14] and an enhanced version of the Random Walk model [16]. For both of the mobility models, the pause time is kept at 0 to produce continuous movement. The speed of a mobile node is uniformly distributed over $[v_{min}, v_{max}]$, where v_{min} is fixed at 3.5m/s and v_{max} ranges between 5m/s and 40m/s.

A mobile node measures the distance to its one-hop neighbors and exchanges this information with all of its neighboring nodes at intervals of $\Delta t = 1$ second. The estimates of inter-node distance have measurement noise that are modeled by a zero-mean Gaussian distribution with variance σ_ϵ^2. The maximum value of σ_ϵ is set to be 4m, which is reasonable for off-the-shelf products [13]. The mobility estimations are carried out in a duration of 900 seconds starting after 1050 seconds of warm-up period.

In the figures generated from the simulation results, each data point corresponds to a mean of 30 repeated experiments with different random seeds.

B. Experimental Results

1) Experiment 1: The first experiment is to compare the speed estimates produced by the proposed scheme, the Link Prediction Algorithm *LPA* [11] and the actual results collected from simulations. In this experiment, the mobility model is fixed as Random WayPoint[4] and the side length of the network area $\mathcal{L}$ is 800m. The maximum speed limit v_{max} is increased from 5m/s to 40m/s (with a step of 5m/s). The inter-node relative speed is estimated using the *RVEd* and the LPA methods. Given a fixed 2m of σ_ϵ, the predicted results as well as the actual values measured with the localization module of the simulator are given in Fig.4. As shown in Fig. 4, the *RVEd* estimator performs much better than the *LPA* method in terms of prediction accuracy regardless of the speed limits.

In order to examine the robustness of the *RVEd* and the *LPA* methods in noisy environments, we further compared the performance of the two methods (in terms of the normalized bias between their estimates and the true values) against various noise levels by increasing σ_ϵ from 0.5m to 4m. The Normalized Bias of the speed Estimates (NBE) is given by:

$$NBE = \frac{E[\hat{v}]}{\bar{v}} - 1 \tag{9}$$

where $\bar{v}$ is the mean of the true values of relative velocities measured from simulation and $E[\hat{v}]$ is the mean of the velocity estimates. NBE indicates how close the speed estimates are to the true values. The results collected from both low (v_{max}=10m/s) and high mobility scenarios (v_{max}=30m/s) are plotted in Fig.5. From Fig.5, we can observe that the *LPA* method is sensitive to both the levels of noise and nodal mobility. The normalized bias of its estimates can be up to 2. Whereas the *RVEs* method demonstrates significant accuracy by limiting the normalized bias within the range of [-0.06, 0.06] in all the scenarios of various noise deviations or speed limits.

2) Experiment 2: The second experiment is to compare the epoch time estimated by the proposed scheme with the actual values measured with the integrated localization module in the simulations. Both the Random WayPoint and the Random Walk mobility models are involved in this experiment. In these two models, mobile nodes are bounced back when they reach the boundary of the network area.

For the scenarios of Random WayPoint mobility, the side length of the network area is varied from 400m to 800m for an increasing length of average epochs. The average duration of actual epochs in the network and the estimates provided by the proposed scheme are given in Fig.6. As shown in Fig.6, the actual values of average epoch time agree with their estimates regardless of the speed limits or the side lengths. In the scenarios with 400m and 600m of side lengths the estimates seems to be slightly overestimated. This may due to that in smaller areas mobile nodes are bounced back more often, which decreases the accuracy of the proposed method.

[4]The results obtained for the Random Walk model are not presented here as the *RVEd* estimator is independent of the mobility model that mobile nodes are following.

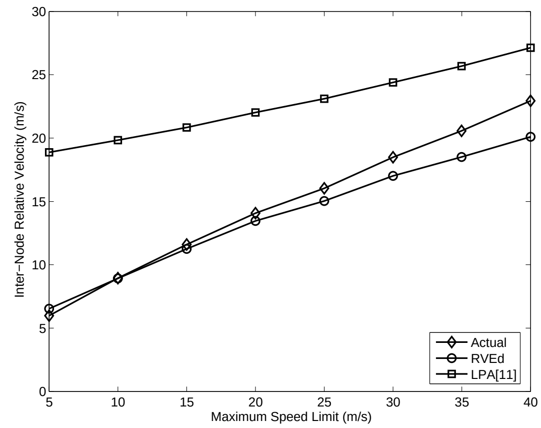

Fig. 4. Inter-node Relative Speed Vs. Maximum Speed Limit ($\sigma_\epsilon = 2m$)

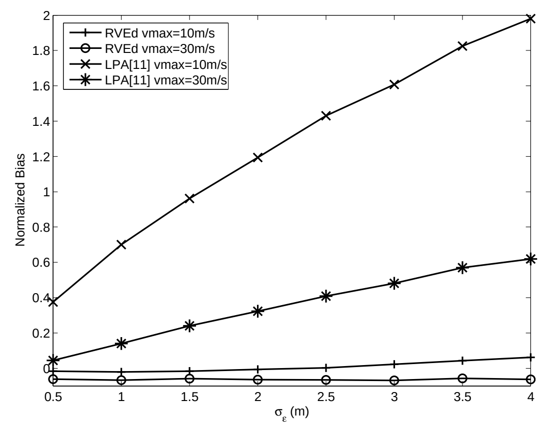

Fig. 5. Normalized Bias of the Range-Based Velocity Estimator Vs. the Standard Deviation of Noise

In the Random Walk model, the epochs of a mobile's movement is exponentially distributed with a mean of ψ. Fig.7 gives the actual and estimated epoch time in scenarios of Random Walk mobility with various speed limits and mean epoch time (e.g. 20s, 40s and 60s). We can see from Fig.7 that the estimates produced by the proposed scheme match the actual values again with the Random Walk mobility. It should be noted that both the measured and the estimated epoch time are shorter than the specified mean ψ. This is because a mobile often starts a new epoch even the current one is not finished due to that it has reached the network boundary and is being reflected back. The frequency of such "reflections" is increasing with the nodal speed.

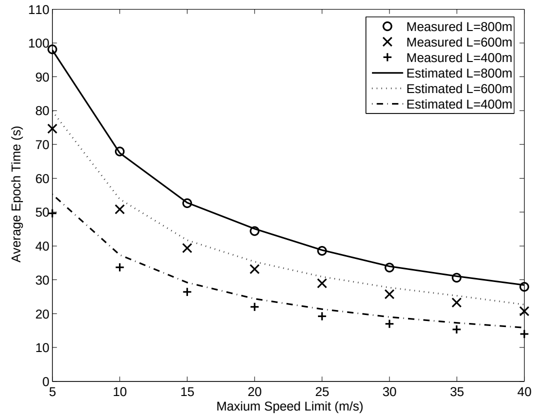

Fig. 6. Average Epoch Time Vs. Maximum Speed Limit, Random WayPoint Mobility

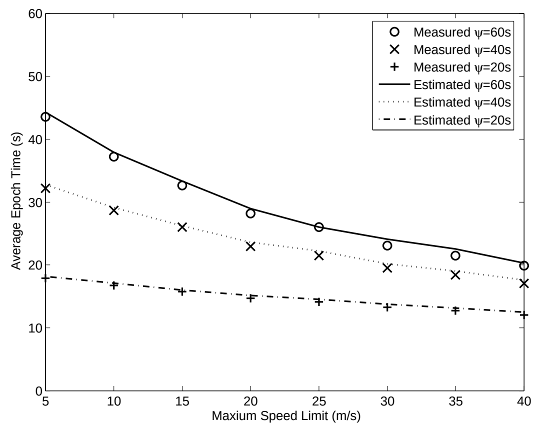

Fig. 7. Average Epoch Time Vs. Maximum Speed Limit, Random Walk Mobility

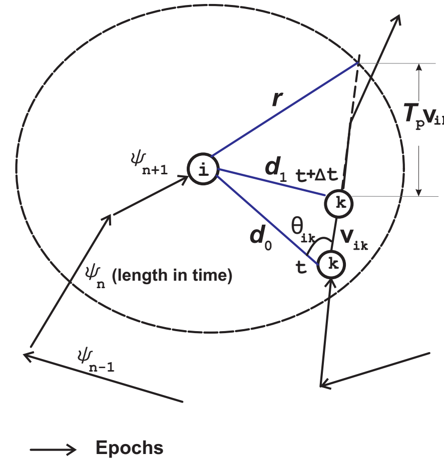

Fig. 8. Epochs and Link Duration Resulted from Node *i* and *k*'s movements

IV. Link Duration and Availability Estimations With $\langle V, \Theta, \Psi \rangle$

In this section, we applies the proposed mobility estimation scheme to a tool of link availability prediction presented in [2]. The purpose is to demonstrate that the proposed scheme can be used to provide networking tools/protocols with mobility information (e.g. relative speeds and epoch distributions) that are normally obtained from complex localization/movement tracking systems or assumed to be known *a priori*.

A. the Prediction-Based Link Availability Estimation

Jiang et al. [2] proposed the prediction-based link availability estimation, which involves two consecutive stages: firstly, the estimation of the projected link life time (denoted as T_p), which is the continuous period from the time when the estimation is made until the link is broken, assuming the relative speed and orientation are constant during this period. Secondly, as the real link life may not really last to T_p if either of the two nodes changed their epochs (see Fig.8), the prediction of the probability (denoted as $L(T_p)$) that the real link life will be T_p or over.

For estimating the projected link life time T_p between two nodes (e.g. node *i* and *k* in Fig.8), the authors in [2] recommended the use of velocity information obtained from GPS or a measurement-based prediction using 3 samples of the inter-node distance. For the prediction of $L(T_p)$ between *i* and *k*, one can use the following expression proposed in [2]:

$$L(T_p) = L_1(T_p) + L_2(T_p, \phi) \tag{10}$$

where $L_1(T_p)$ represents the case that neither of the two nodes changed their epochs within time T_p. Let $\mathcal{A}_i(x) = \mathcal{P}\{\psi \leq x\}$ denote CDF of node *i*'s epoch time. For a link connecting node *i* and *k*, $L_1(T_p)$ is given by:

$$L_1(T_p) = \mathcal{A}_i(T_p)\mathcal{A}_k(T_p) \tag{11}$$

$L_2(T_p, \phi)$ represents the case that either of the two nodes change their velocities at time ϕ within T_p ($\phi < T_p$). $L_2(T_p, \phi)$ can be calculated as [2]:

$$L_2(T_p, \phi) = \frac{\phi + p(T_p - \phi)\mathcal{A}_i(T_p - \phi)\mathcal{A}_k(T_p - \phi)}{T_p} + \varepsilon \tag{12}$$

where *p*=0.5 is the simplified probability that the two nodes will approach each other after an epoch change occurs. ε is an estimate of the probability that there are more than 1 epoch changes since ϕ (within T_p) and the contributes of these epoch changes to the link availability is positive. The value of ε is suggested to be measured in realtime due to the difficulty of its exact calculation [2].

B. Estimating Link Durations with V and Θ

With the mobility parameters $\langle V, \Theta, \Psi \rangle$ estimated by the proposed scheme, we can approximate the projected link life T_p within 2 time slots, instead of 3 as suggested in [2] and [11]. This shortens the amount of time that a mobile needs to wait until it can have an estimation of T_p, especially when the inter-node distances are sampled over long time intervals.

As shown in Fig.8, d_0 and d_1 are the distance estimates between *i* and *k* sampled at time *t* and $t+\Delta t$, respectively. v_{ik} ($v_{ik} \in V_i$) is the relative speed and θ_{ik} ($\theta_{ik} \in \Theta_i$) the relative orientation between *i* and *k* estimated at $t + \Delta t$. According to the *Cosine Rule*, we have the following equation:

$$cos\hat{\theta}_{ik} = \frac{d_0^2 + (T_p + \Delta t)^2 \hat{v}_{ik}^2 - r^2}{2d_0(T_p + \Delta t)\hat{v}_{ik}} \tag{13}$$

As $T_p + \Delta t > 0$, the projected link life time T_p between node *i* and *k* can be derived from Eq.(13) as:

$$T_p = \frac{\sqrt{d_0^2 cos^2\hat{\theta}_{ik} - \hat{v}_{ik}^2(r^2 - d_0^2)} + d_0 cos\hat{\theta}_{ik}}{\hat{v}_{ik}^2} - \Delta t \quad (14)$$

C. Link Availability Predictions with Ψ

In [2] and [3], the authors assumes that the distributions and the mean length of epochs are known to a mobile node. This assumption is unrealistic as the network configurations are normally not known to a mobile especially to those just joined the network. With the proposed scheme of mobility estimations, a mobile can now approximate the epoch lengths and distributions in networks of unknown configurations, without the help of any movement tracking systems. If a mobile node (e.g. *i*) has recorded sufficient number (e.g. over 30 [17]) of its past epoch time, it can estimate the CDF of its epochs for Eq.11 and Eq.12 as follows:

$$\mathcal{A}_i(x) = \mathcal{P}\{\psi \leq x\} = 1 - \frac{|\Psi_i^x|}{|\Psi_i|} \quad (15)$$

where the subset $\Psi_i^x = \{\psi \in \Psi_i \wedge \psi > x\}$. For the calculation of $L_2(T_p)$ using Eq.12, an expected time ϕ at which first epoch change occurs within T_p (denoted as $\bar{\phi}$) can be also approximated in realtime as:

$$\bar{\phi} = \frac{1}{|\Psi_i^s| + |\Psi_k^s|}\Big(\sum_{\psi_i \in \Psi_i^s} \mathcal{F}(\psi_i, \tau_i) + \sum_{\psi_k \in \Psi_k^s} \mathcal{F}(\psi_k, \tau_k)\Big) \quad (16)$$

where the subset $\Psi_i^s = \{\psi \in \Psi_i \wedge \psi < T_p + \tau_i\}$, τ_i denotes the elapsed time of current epoch of *i* [5], and $\mathcal{F}(\psi, \tau) = \psi - \tau$ $(\psi > \tau)$ or 0 $(\psi \leq \tau)$. We denote the link availability estimation based on the realtime estimation of $\langle V, \Theta, \Psi \rangle$ as $L_{rt}(T_p, \Psi)$. We have $L_{rt}(T_p, \Psi) = L_1(T_p, \Psi) + L_2(T_p, \Psi)$.

Note that in a network where the distribution of epochs of a node is homogeneous, Ψ_i can be approximated by Ψ_k in the above equations, and vice versa.

D. Preliminary Results

In a third experiment, we test the performance of link availability predictions with mobility parameters (e.g. $\langle V, \Theta, \Psi \rangle$) estimated by the proposed scheme in networks with Random Waypoint or Random Walk mobility. For each estimated T_p we measured the actual residual link life time (denoted as T_r). The resulting T_r/T_p is the actual link availability. Similar to [2], let $L_{min}(T_p, \Psi) = L_{rt}(T_p, \Psi) - \varepsilon$ be the conservative link availability without considering the factors represented by ε. From *m* pairs of $(T_r/T_p, L_{min})$ of different values collected from simulations, we measure ε as:

$$\varepsilon = \frac{1}{m}\sum_{j=1}^{m}\Big(\frac{T_{r,j}}{T_{p,j}} - L_{min}(T_{p,j}, \Psi_{i,j})\Big) \quad (i \in \mathcal{N}) \quad (17)$$

[5]Denoted as *Curr_Epoch_Elapsed* in the pseudo code listed in Fig.3.

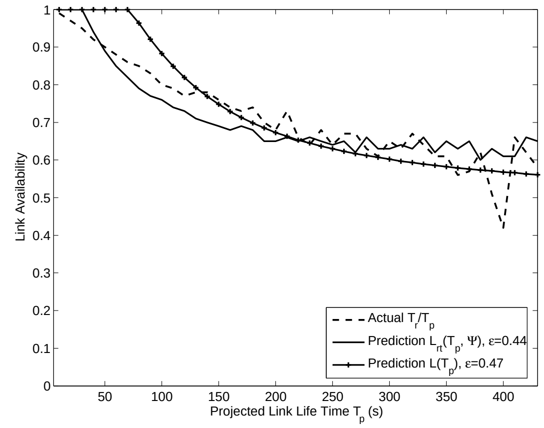

Fig. 9. Predicted Residual Link Life Time Vs. Link Availability, Random WayPoint Mobility $\mathcal{L} = 800m$

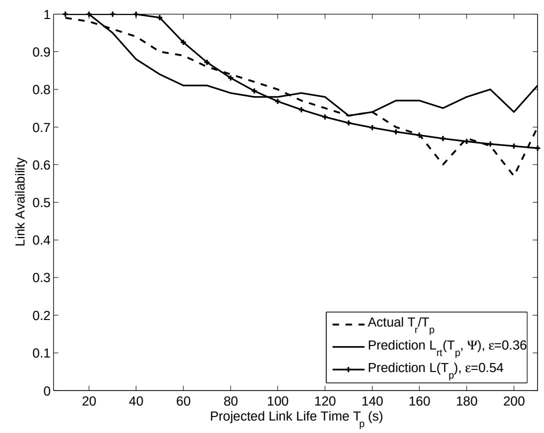

Fig. 10. Predicted Residual Link Life Time Vs. Link Availability, Random Walk Mobility ψ= 45s

Fig.9 and Fig.10 plot the 10s averages[6] of the actual link availability T_r/T_p and those of $L_{rt}(T_p, \Psi)$, as well as $L(T_p)$ with artificially given parameters [2] for Random WayPoint and Random Walk mobility, respectively. Note that the values of $L_{rt}(T_p, \Psi)$ and $L(T_p)$ that are bigger than 1 after adding ε are approximated as 1. As shown in both Fig.9 and Fig.10, the performance of the realtime prediction $L_{rt}(T_p, \Psi)$ is comparable to that of $L(T_p)$. In Fig.9 when T_p is between 150s and 350s, the curve of $L_{rt}(T_p, \Psi)$ even has similar fluctuating tendency with that of actual results. In some cases when the actual link availability drops, as those observed at T_p over 350s in Fig.9 or at T_p over 160s in Fig.10, $L_{rt}(T_p, \Psi)$ does not match well with the reality. This is due to the fact that there are less data collected from the simulated network when T_p is large while ε is an average of many events making $L_{rt}(T_p, \Psi)$ more accurate for frequently occurring events. A similar phenomenon and its explanation can be found in [2].

[6]As $L_{rt}(T_p, \Psi)$ or $L_{min}(T_p, \Psi)$ are based on epoch information collected in realtime, instead of a fixed epoch distribution as in [2], their values are fluctuating as those of T_r/Tp do. 10s averages of these data are plotted to show their tendency while keeping a certain degree of accuracy.

V. Conclusions

In the emerging wireless mobile ad-hoc networks, the topological stability has significant impact on the quality of communications. Knowledge of the mobility of mobiles, such as their relative speeds and orientations as well as their epoch time, is important as these parameters are closely correlated with the frequency of topological reconfigurations in the network. Conventional ways of measuring the nodal mobility involves complex localization systems such as the costly GPS or statistical approaches that rely on precise knowledge of the characteristics of signal propagation. In this paper, based on our recent study on range-based velocity estimations, we propose a new scheme to estimate in realtime the mobility of a mobile node (e.g. its relative speeds and orientations to its neighbors and its past epoch time) using only the time-varying inter-node distance information. Represented by a triplet $\langle V, \Theta, \Psi \rangle$, these mobility parameters are directly correlated to the stability of networks. In contrast to existing methods, the proposed scheme is less dependent on signal characteristics and is more robust in noisy environments. The performance of the proposed scheme is validated by computer simulations against an existing method in scenarios of various speed limits. As an application example, the proposed scheme is applied to an existing tool to provide mobility information for predicting link availability. Preliminary results from various network scenarios show that, with the proposed scheme, the tool achieved a comparable performance to when hard-coded parameters are used.

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Appendix

Determining the relative speed to a *departing node*

When a node is passing through a neighboring node's radio coverage, its distance to the neighboring node is first decreasing before it reaches the closest point and then increasing until it exceeds the node radio radius. We refer a node's neighbors whose distance is increasing as *departing nodes*. If this node does not change its path when it is passing by this neighbor, it's trajectory is a strait line and is perpendicular to the closet distance between these two nodes. As shown in Fig.11, d_e is node *i*'s true distance to node *j* at the time when *j* reached *i*'s radio coverage. $\hat{d}_e$ is its estimate. $\hat{d}_{p-1}$, $\hat{d}_p$ and $\hat{d}_{p+1}$ are the distance estimates sampled at consecutive time slots (e.g. $t_p - \Delta t$, t_p and $t_p + \Delta t$). $\hat{d}_p$ can be used to approximate the closest distance between node *j*'s trajectory and node *i* if it satisfies $\{\hat{d}_{p-1} > \hat{d}_p \wedge \hat{d}_{p+1} > \hat{d}_p\}$, assuming this relationship is not affected by measurement noise.

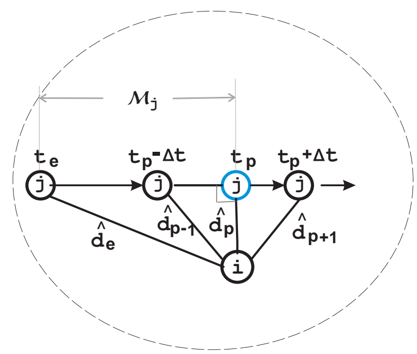

Fig. 11. Estimation of relative velocity - the *RVEs* method

Let $\mathcal{M}_j$ be the movement of *j* relative to *i* from time t_e to time t_p, we have $\mathcal{M}_j = v_{ij}(t_p - t_e)$. According to the theorem of Pythagoras, we can obtain $\hat{v}_{ij}$, the estimate of v_{ij}, by:

$$\hat{v}_{ij} = \frac{\mathcal{M}_j}{t_p - t_e} = \frac{\sqrt{\hat{d}_p^2 - \hat{d}_e^2}}{t_p - t_e} \tag{18}$$