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Location Management Cost Estimation for Ad Hoc Mobile Networks with Missing Measurements[1]

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Abstract— **In an ad hoc mobile network, mobile users travel at variable velocity. The measurement of the motion velocity of a mobile user may not be consecutive due to possible missing observations. This paper presents an approach to the total cost estimation of variable velocity mobile location management for ad hoc mobile networks with missing measurements. Since the change of a mobile's velocity within a short time period is limited due to physical restrictions, a mobile user's future velocity is likely to be correlated with its past and current velocity. We propose to use the Gauss–Markov mobility model to capture the correlation of a mobile's velocities. A Kalman filter of a linear uncertain discrete stochastic system is designed to estimate the total cost, and the formulas for calculating the steady state covariance of the estimation error of total cost are presented. A numerical example is given to illustrate the use of the proposed approach.**

Index Terms— **Ad Hoc Network, Home Region, Location Management, Kalman Filter**

1. INTRODUCTION

Mobile ad hoc networks consist of wireless hosts that communicate with each other in the absence of a fixed infrastructure. Some examples of the possible uses of ad hoc networking include soldiers on the battlefield, emergency disaster relief personnel, and networks of laptops. Routing a packet from a source to a destination in a mobile ad hoc network is a challenging problem, since nodes in the network may move and cause frequent, unpredictable topological changes. Thus, when two nodes travel apart, they may no longer have a direct link between them. Likewise, if a node moves behind a hill, its links to its neighbors may be severed because of fading. Other reasons for changes in topology include jamming and the entry of new nodes to the network or departure of the existing nodes from the network.

Location management enables the ad hoc network to track the locations of users and their terminals between call arrivals. Since mobile users are free to move within the coverage area, the network can only maintain the approximate location of each user. When a connection needs to be established for a particular user, the network has to determine the user's exact location within the defined granularity. Location management for an ad hoc network contains three components: *location update*, *maintaining home regions*, and *locating a node packet*. The operation of informing the home region about the current location of the mobile user is known as location update or location registration, and the messaging cost (packets/second) of performing these activities is the *cost of location update*. When a node moves from region *A* into region *B*, it needs to inform nodes in region *A* of its departure and meanwhile, it needs to inform nodes in region *B* of its arrival. It also needs to collect location information about all the nodes registered in region *B*. The operation of these activities is known as maintaining home regions, and the messaging cost (packets/second) of performing these activities is the *cost of maintaining home regions*. When a node receives a data packet from some destination, it needs to find the current location of the destination before sending packets to it. The operation of determining the location of the mobile user is called terminal locating or paging, and the messaging cost (packets/second) of performing these activities is the *cost of locating a node*.

Several approaches have been proposed to address ad hoc network routing and costs [1-4]. In [4] a scalable routing protocol is presented. This protocol relies on a location update mechanism that maintains approximate location information for all nodes in a distributed pattern. As nodes move, this approximate location information is constantly updated. To maintain the location information in a decentralized way, this paper maps a node ID to a geographic sub-region of the network. Any node present in this sub-region is then responsible for storing the current location of all the nodes mapped to this sub-region. In order to send packets to a node, the sender first queries the destination's sub-region for the approximate location of the destination, and then uses a simple geographic routing protocol to forward the packets to the destination's approximate location. It is therefore easy to see that there is location update cost in this protocol that is dependent on the speed of node movement. In [5], the authors discuss the routing overhead or total cost of location management in the situation that the motion speed of a mobile node is constant or at average value.

Mobile users' movement is generally confined to a limited geographical area. The motion velocity of a mobile node is *variable*. Furthermore, the change of a mobile's velocity within a short time can be limited due to physical restrictions. Therefore, a mobile user's future velocity is variable and likely to be correlated with its past and current velocity. The Gauss–Markov model [6] represents a wide range of user mobility patterns, including, as its two extreme cases, the random walk [7], [8] and the constant velocity fluid-flow models. Since it captures the essence of the correlation of a mobile's velocities in time, we use it to specify the characteristics of mobile node movement.

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In the real world, on the other hand, the measurements of mobile motion velocity are not consecutive due to occasionally missing observations which are caused by a variety of reasons. The examples are a certain failure in the measurement, intermittent sensor failures, accidental loss of some collected data, and some of the data may be jammed or coming from a high-noise environment [9]. For these reasons, this paper presents an approach to the total cost estimation of variable velocity mobile location management for ad hoc mobile networks with missing measurements. The key to the cost estimation is the design of an estimator. A Kalman filter of linear uncertain discrete stochastic system with missing measurement is thus developed to serve this purpose.

The rest of the paper is organized as follows. In Section 2, we describe a Gauss–Markov mobility model, which is a linear uncertain discrete-time stochastic system. Section 3 evaluates the total cost of location management based on the model. The design of the Kalman filter of a linear uncertain discrete stochastic system with missing measurement is studied in Section 4. A numerical example is presented in Section 5. Section 6 concludes the paper.

2. GAUSS–MARKOV MODEL FOR MOBILE MOVEMENT

Mobile nodes often have to change speed during the course of motion. We assume that mobile nodes move at inconstant velocity and the velocity change follows a Gauss–Markov process. According to [6], the 1-D discrete version of the Gauss-Markov mobility model can be described as:

$$v_n = \alpha v_{n-1} + (1-\alpha)\mu + \sigma\sqrt{1-\alpha^2}\,w_{n-1} \tag{1}$$

where v_n is a mobile velocity during the n-th period, α the memory level, which reflects the relationship between v_{n-1} and v_n, μ the mean of v_n, σ^2 the variance of v_n, and w_n an uncorrelated Gaussian process with zero mean, unit variance. w_n is independent of v_n.

Let $u_n = v_n - \mu$, $\beta = \sigma\sqrt{1-\alpha^2}$. Eq. (1) can be rewritten in the following simple and clear form:

$$u_{n+1} = \alpha u_n + \beta w_n \tag{2}$$

3. TOTAL LOCATION MANAGEMENT COST ESTIMATION

In this section, we discuss how to evaluate the total location management cost. We assume that the ad hoc network under study is in a rectangular region; all nodes in the network are equipped with Global Positioning System (GPS) that provides them with their current location; they are aware of the identities of their neighbors; and each node has a unique ID (such as an IP address). We use the following notations in this section:

- N number of nodes
- a area of region
- b broadcast cost in a region
- ■ number of region crossings per second per node
- v speed (meters per second)
- ϕ average number of nodes in a region
- $2R \times 2R$ region size
- u cost of sending location update message to home region
- δ cost of collecting location information

Note that for the simplicity of analysis we sometimes approximate square regions ($2R \times 2R$) by circles of diameter $2R$. This approximation is done to make the expressions more manageable and is deemed as reasonable [4].

3.1 Cost of Location Update

When a node moves into a new region, it generates a location update message and sends the message to its home region. Upon arriving at the node's home region, the location update message is broadcast to all other nodes within that region. The cost of location update is

$$c_u = ■(b+u) \tag{3}$$

which is measured in the unit of number of packets per second. It follows Theorem 1 in [4] that the average update cost is

$$\bar{c}_u \approx (K_1\sqrt{N} + K_0)v \tag{4}$$

where $K_0 = \dfrac{\pi R}{4}$, $K_1 = \dfrac{\pi}{4}\sqrt{\dfrac{1}{\phi}}$.

3.2 Cost of Maintaining Home Regions

When a node moves from region A into region B, it needs to inform nodes in region A that it has left and meanwhile, it needs to inform nodes in region B of its arrival. It also needs to collect location information about all the nodes registered in region B. The messaging cost (packets/second) of performing these activities is denoted by c_m and calculated by

$$c_m = N\rho(2b+\delta) \tag{5}$$

Based on Theorem 2 in [4], the mean cost of maintaining home region is

$$\bar{c}_m \approx K_2 N v \tag{6}$$

where $K_2 = \dfrac{\pi}{4R}(2R^2+\delta)$. In the worst case, the new node would get as many as ϕ duplicate responses to its request for this information (recall that ϕ is the average number of nodes within a region). In the best case, only one node would respond. Thus, $1 \le \delta \le \phi$.

3.3 Cost of Locating a Node

When a node receives a data packet from some destination, it needs to find the current location of the destination before sending packets to it. This can be done by using MFR, Most Forward with fixed Radius [13]. The cost of finding the location might be zero or a constant if either the node itself or one of its neighbors has the location information available in a cache, which happens if there are several packets destined for the same destination. In our analysis, however, we make the pessimistic assumption that the location information is not cached; therefore, the source node needs to contact the destination node's home region to find the destination's location. The average node locating cost is

$$\bar{c}_l \approx K_3\sqrt{N} \tag{7}$$

where $K_3 = \sqrt{1/\phi}$.

3.4 Total Location Management Cost

After we have estimated each of the individual costs involved in maintaining location information and finding the location information, we can estimate the total cost of routing packets. Assume that packets arrive at *each* node at a rate of λ packets per second according to a Poisson process. Then the average cost of routing N nodes can be calculated as

$$\begin{aligned}\bar{c} &= N\lambda\bar{c}_l + \bar{c}_m + N\bar{c}_u \\ &= \lambda K_3 N\sqrt{N} + K_2 N v + K_1 N\sqrt{N} v + K_0 N v\end{aligned} \tag{8}$$

Recall the assumption that mobile motion process is Gauss–Markovian. Let

$$v_n = u_n + \mu \tag{9}$$

Substituting v in (8) with $v_n = u_n + \mu$, and $\bar{c}$ in (8) with c_n, we obtain

$$\begin{aligned}c_n &= \lambda K_3 N\sqrt{N} + K_2 N v_n + K_1 N\sqrt{N} v_n + K_0 N v_n \\ &= \lambda K_3 N\sqrt{N} + K_2 N(u_n+\mu) + K_1 N\sqrt{N}(u_n+\mu) + K_0 N(u_n+\mu) \\ &= (K_2 N + K_1 N\sqrt{N} + K_0 N)u_n + \lambda K_3 N\sqrt{N} + K_2 N\mu + K_1 N\mu + K_0 N\mu\end{aligned} \tag{10}$$

$$\text{Let}\quad \begin{aligned}\eta &= (K_2 N + K_1 N\sqrt{N} + K_0 N), \\ \kappa &= \lambda K_3 N\sqrt{N} + K_2 N\mu + K_1 N\mu + K_0 N\mu\end{aligned} \tag{11}$$

Then it follows from (10) and (11) that

$$c_n = \eta u_n + \kappa \tag{12}$$

4 FILTER DESIGN WITH MISSING MEASUREMENT

Note that Eq. (12) for the total location management cost estimation is obtained without considering the possibility of missing measurements. In that case we can easily compute the expectation and covariance of c_n. In this section, we discuss the estimation of the total location management cost with missing measurements. We utilize the Kalman filter to deduce the steady covariance of the estimation error of total cost per unit time.

With missing measurements, Eq. (12) takes the following form:

$$c_n = \gamma_n \eta u_n + \kappa \tag{13}$$

where γ_n is a Bernoulli distributed white sequence. γ_n is assumed to be independent of w_n, u_0, and is either 0 or 1 with

$$\mathrm{Prob}\{\gamma_n = 1\} = \bar{\gamma} \tag{14}$$

where $\bar{\gamma}$ is a known positive constant. Denote by $\hat{u}_n$ the estimate of u_n. Let

$$\tilde{\gamma}_n = \gamma_n - \bar{\gamma} \tag{15}$$

$$e_n = u_n - \hat{u}_n \tag{16}$$

Then the estimation error of total cost per unit of time is as follows

$$\begin{aligned}\tilde{c}_n &= c_n - (\bar{\gamma}\eta\hat{u}_n + \kappa) \\ &= (\gamma_n \eta u_n + \kappa) - (\bar{\gamma}\eta\hat{u}_n + \kappa) \\ &= \bar{\gamma}\eta e_n + \tilde{\gamma}\eta u_n\end{aligned} \tag{17}$$

The linear filter considered in this paper is of the following structure:

$$\hat{u}_{n+1} = g\hat{u}_n + q\tilde{c}_n \tag{18}$$

where g and q are the filter parameters to be scheduled. Subsequently, the state error is given as

$$\begin{aligned}e_{n+1} &= u_{n+1} - \hat{u}_{n+1} \\ &= (\alpha - g - q\tilde{\gamma}\eta)u_n + (g - \bar{\gamma}q\eta)e_n + \beta w_n\end{aligned} \tag{19}$$

Define

$$x^f_{n+1} = \begin{pmatrix} u_{n+1} \\ e_{n+1} \end{pmatrix}$$

$$A = \begin{pmatrix} \alpha & 0 \\ \alpha - g - \eta q\tilde{\gamma} & g - \eta q\bar{\gamma} \end{pmatrix}$$

$$B = \begin{pmatrix} \beta & 0 \\ 0 & \beta \end{pmatrix}$$

$$w^f_n = \begin{pmatrix} w_n \\ w_n \end{pmatrix}$$

Based on (2) and (19) we obtain the following augmented system:

$$x^f_{n+1} = Ax^f_n + Bw^f_n \tag{20}$$

Let

$$X^{uu}_n = E[u_n u_n^T],\ X^{ue}_n = E[u_n e_n^T]$$

$$X^{eu}_n = E[e_n u_n^T],\ X^{ee}_n = E[e_n e_n^T]$$

Then we have

$$X_n = E[x^f_n (x^f_n)^T] = \begin{pmatrix} X^{uu}_n & X^{ue}_n \\ X^{eu}_n & X^{ee}_n \end{pmatrix} \tag{21}$$

Note that

$$E[w^f_n (w^f_n)^T] = \begin{pmatrix} 1 & 1 \\ 1 & 1 \end{pmatrix} = E_0 \tag{22}$$

It follows from (20), (21) and (22) that

$$X_{n+1} = AX_n A^T + BE_0 B^T \tag{23}$$

Denote the steady-state covariance by X , i.e.

$$X \triangleq \lim_{n\to+\infty} X_n \tag{24}$$

According to [11, 12], if the state of (23) is mean square bounded, then X exists and satisfies the following discrete-time modified Lyapunov equation:

$$X = AXA^T + BE_0 B^T \tag{25}$$

Theorem 1: Suppose that the state in (23) is mean square bounded and the memory level $\alpha < 1$. There exists a unique symmetric positive-semidefinite solution to (25) if and only if the Kalman filter parameters g and q satisfy

$$\left|g - q\bar{\gamma}\eta\right| < 1 \tag{26}$$

Proof: It follows from (10) that, there exists a unique symmetric positive-semidefinite solution to (25) if and only if

$$\rho\{A \otimes A\} < 1 \tag{27}$$

where, ρ is the spectral radius and $\otimes$ is the Kronecker product. Because

$$A \otimes A = \begin{pmatrix} \alpha^2 & 0 \\ (\alpha - g - \eta q\tilde{\gamma})^2 & (g - \eta q\bar{\gamma})^2 \end{pmatrix} \tag{28}$$

the constraint of (27) is equivalent to

$$\max\{\alpha^2, (g - q\eta\bar{\gamma})^2\} < 1 \tag{29}$$

Also because it is assumed that $\alpha < 1$, the constraint can be further simplified to

$$\left|g - q\eta\bar{\gamma}\right| < 1 \tag{30}$$

This completes the proof of the theorem. ■

Theorem 2: The covariance of estimation error of total cost is equivalent to the variance of the estimation error of the state in Eq.(2), in other words $\tilde{C}_n = (\eta\bar{\gamma})^2 X_n^{ee}$

Proof: We know from (17) that

$$\tilde{c}_n = \bar{\gamma}\eta e_n + \tilde{\gamma}\eta u_n = \begin{pmatrix} \tilde{\gamma}\eta & \bar{\gamma}\eta \end{pmatrix} \begin{pmatrix} u_n \\ e_n \end{pmatrix} \tag{31}$$

Let

$$\Psi \triangleq \begin{pmatrix} \tilde{\gamma} \\ \bar{\gamma} \end{pmatrix} \tag{32}$$

Then we can rewrite (31) as

$$\tilde{c}_n = \begin{pmatrix} \tilde{\gamma}\eta & \bar{\gamma}\eta \end{pmatrix} \begin{pmatrix} u_n \\ e_n \end{pmatrix} = \eta \Psi^T x_n^f \tag{33}$$

Then covariance of estimation error of total cost per unit of time follows as

$$\tilde{C}_n = \varepsilon[\tilde{c}_n(\tilde{c}_n)^T] = \eta^2 \varepsilon(\Psi^T x_n^f (x_n^f)^T \Psi) \tag{34}$$

Since γ_n and u_n are uncorrelated and γ_n is white noise sequences, we obtain from (34) that

$$\begin{aligned} \tilde{C}_n &= \eta^2 \varepsilon(\Psi^T x_n^f (x_n^f)^T \Psi) \\ &= \eta^2 \begin{pmatrix} 0, \bar{\gamma} \end{pmatrix} \begin{pmatrix} X_n^{uu} & X_n^{ue} \\ X_n^{eu} & X_n^{ee} \end{pmatrix} \begin{pmatrix} 0 \\ \bar{\gamma} \end{pmatrix} \\ &= (\eta\bar{\gamma})^2 X_n^{ee} \end{aligned} \tag{35}$$

The theorem is proved. ■

We obtain the following two corollaries from the above theories:

Corollary 1: If $\alpha < 1$ and parameters g and q in the filter (18) satisfy (26), then the steady state covariance of estimation error of total cost per unit of time exists and satisfies (25).

Proof: Based on Theorem 1, if $\alpha < 1$ and parameters g and q satisfy (26), there exists a unique symmetric positive-semi-definite solution to (25). In other words, the limit $\lim_{n\to+\infty} X_n^{ee}$ exists. It results from the relation of $\tilde{C}_n$ and X_n^{ee} in Theorem 2 that the limit $\lim_{n\to+\infty} \tilde{C}_n$ exists. The corollary is proved. ■

Now, let us examine how to calculate the steady covariance of estimation error

Corollary 2: Let $\tilde{C} \triangleq \lim_{n\to+\infty} \tilde{C}_n, \varepsilon \triangleq g - \eta q\bar{\gamma}$. If the state of (23) is mean square bounded, $\alpha < 1$ and $\varepsilon < 1$, then the steady covariance of estimation error of total cost per unit of time

$$\tilde{C} = \frac{(\eta\beta\bar{\gamma})^2}{(1-\varepsilon\alpha)} \tag{36}$$

Proof: If the state of (23) is mean square bounded, $\alpha < 1$ and $\varepsilon < 1$, then, it follows directly from Theorem 1 and the Lyapunov equation (25) that

$$X^{ee} = \frac{\beta^2}{(1-\varepsilon\alpha)} \tag{37}$$

Eq. (36) can be obtained by solving (37), $\tilde{C}_n = (\eta\bar{\gamma})^2 X_n^{ee}$ in Theorem 2 and $\tilde{C} \triangleq \lim_{n\to+\infty} \tilde{C}_n, X^{ee} = \lim_{n\to+\infty} X_n^{ee}$. This completes the proof of this corollary. ■

5 NUMERICAL EXAMPLE

In this section, we demonstrate how to design the Kalman filter through an example.

Consider an ad hoc network with 100 mobile nodes (N= 100). The velocity v_n of a mobile user is a Gauss–Markov process with mean $\mu = 1.2m/s$ and memory level $\alpha = 0.8$. The variance of v_n is $\sigma^2 = 0.99$. The region size is specified by $R = 100m$, hence the area $a = 40000m^2$. The average number of nodes in a region is 9 ($\phi = 9$). The packet rate is $\lambda = 2$ packets per second. The cost of collecting location information about nodes registered in the new region is $\delta = 5$. The probability for complete observation is assumed to be 0.6, i.e. $\bar{\gamma} = 0.6$. Based on these inputs we can calculate according to (11) that $\eta \approx 7583\pi$. Substituting $\eta \approx 7583\pi$ and $\bar{\gamma} = 0.6$ into (26) gives $|g - 4550\pi q| < 1$. This is the constraint to guide the design of the Kalman filter.

We want to get the filter parameters, g and q, such that the steady covariance of estimation error of total cost per unit time satisfies $\tilde{C} < 500$. Let $q = \frac{1}{455\pi}$ and $g = 10.5$, then $\varepsilon = g - q\eta\gamma = 0.5$. It follows from Eq. (36) that the estimation error of total cost per unit time is $\tilde{C} = \frac{(\eta\beta\bar{\gamma})^2}{(1-\varepsilon\alpha)} = \frac{(7583\pi \times 0.6 \times 0.02)^2}{1 - 0.5 \times 0.8} \approx 476.2$. The average total cost per unit time, calculated based on Eq. 11, is κ = 207938.1 packets per second.

Discussion: This example shows how to estimate location management cost for ad hoc networks with missing measurements. Without loss of generality, we use Most Forward with fixed Radius Protocol for locating a node packet. The average cost of finding the location c_l might be zero or a constant if either the node itself or one of its neighbors has the location information available in a cache. In our analysis, however, we make the pessimistic assumption that the location information is not cached. Therefore, the source node needs to contact the destination node's home region to find the destination's location, and the cost is given by Eq. (7).

According to Corolllary 2, if the memory level $0 \le \alpha < 1$ and $\left| g - q\eta\bar{\gamma} \right| < 1$, the steady covariance of estimation error of total cost per unit of time $\tilde{C} = \dfrac{(\eta\beta\bar{\gamma})^2}{(1-\varepsilon\alpha)} = \dfrac{(\eta\sigma\bar{\gamma})^2(1-\alpha^2)}{1-(g-\eta q\bar{\gamma})\alpha}$, then $\lim_{\alpha\to 0}\tilde{C} = (\eta\sigma\bar{\gamma})^2$, $\lim_{\alpha\to 1}\tilde{C} = 0$, and $\lim_{\gamma\to 0}\tilde{C} = 0$, $\lim_{\gamma\to 1}\tilde{C} = \dfrac{(\eta\beta)^2}{(1-\varepsilon\alpha)}$. We can see from this example that the approach proposed possesses both effectiveness and flexibility.

6 CONCLUSION

This paper discusses the total cost estimation of mobile location management for ad hoc mobile networks with missing measurements. Mobile nodes are assumed to move at variable velocity. Considering the fact that the change of a mobile's velocity within a short time period is necessarily limited due to physical restrictions, which leads a mobile node's future velocity to be correlated with its past and current velocity, we propose to use a Gauss–Markov mobility model to capture the correlation of a mobile's velocities. A Kalman filter of a linear uncertain discrete stochastic system is designed to estimate the total cost, and the formulas for steady state covariance of the estimation error of total cost computation are presented. The design of the proposed Kalman filter is illustrated by a numerical example.

Possible future research directions to location management in ad hoc mobile network include location management for sensor delay with measurement missing ad hoc networks, location management for special routing protocols, and location management for QoS of mobile decision support in ad hoc mobile network.

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