Mobility Modelling and Trajectory Prediction for Cellular Networks with Mobile Base Stations *

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ABSTRACT

This paper provides mobility estimation and prediction for a variant of GSM network which resembles an adhoc wireless mobile network where base stations and users are both mobile. We propose using Robust Extended Kalman Filter (REKF) as a location heading altitude estimator of mobile user for next node (mobile-base station) in order to improve the connection reliability and bandwidth efficiency of the underlying system. Through analysis we demonstrate that our algorithm can successfully track the mobile users with less system complexity as it requires either one or two closest mobile-basestation measurements. Further, the technique is robust against system uncertainties due to inherent deterministic nature in the mobility model. Through simulation, we show the accuracy and simplicity in implementation of our prediction algorithm.

Categories and Subject Descriptors

C.2 [**Computer-Communication networks**]: Network Architecture and Design —*Wireless communication*

General Terms

Algorithms, Measurement, Performance, Theory

1. INTRODUCTION

A Mobile Ad Hoc Network (MANET) is a wireless network consisting of mobile nodes capable of communicating with each other without the help of any fixed infrastructure. Mobile Ad Hoc networks date back to the 1970s when they were known as DARPA packet radio networks. Recently there have been renewed interest in such networks due to the availability of smaller, smarter, and cheaper portable computers, inexpensive wireless technology, small wireless sensors, and mobile users' demand for information "any where any time". The IETF has established a special working group for developing standard protocols for such networks [1]. MANETs are self-organizing networks built dynamically in the presence of nodes equipped with radio interface devices. The nodes are capable of movement in an arbitrary fashion. All the functionality of routing and switching are carried out by the nodes themselves. When two nodes are within the communicating range of each other, they can exchange information directly. However, when two nodes are not within each other's communicating range, they can still communicate with each other provided there are nodes in between who can pass the data packets for the communicating nodes. Communication, in this later case, occurs in a multi-hop fashion [2]. These networks are designed for temporary and special use, such as, at battlefield or emergency rescue operation where there may not be any established infrastructure for networking.

Research in MANET has given rise to many new network architectures. The Multihop cellular Architecture [3] provides localized Ad-hoc networking within a cell, where mobile hosts within the cell help each other to forward packets to the base station. By using multihopping, the cellular architecture can expand the cell coverage while maintaining the transmission range of the base station. As a result reduced numbers of base stations are possible. Lin et al [3] used WLAN (802.11) for their experimentation and have shown that the resulting throughput can be higher than for single-hop based networks.

The Terminode project [4] looks at developing a wide-area, autonomous, self-organized, wireless multimedia network that is totally independent of any fixed infrastructure. The Grid project at the MIT Laboratory for Computer Science deployed a test bed network composed of cars - CarNet [5]. The CarNet project attempts to equip all test bed cars with an IEEE 802.11 radio, Linux box and a GPS receiver in order to demonstrate their Grid architecture. The sample services for CarNet might include traffic congestion monitoring, fleet tracking, and highway chat (similar to CB).

High Altitude Aeronautical Platform (HAAP) [6] uses undedicated aircrafts to support mobile coverage. The aircrafts (e.g., Commercial planes) act as satellites to provide city-wide coverage while they are appropriately positioned

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(location and altitude). The HAAP architecture uses redundancies to provide continuous coverage while planes enter or leave the city, or prepare for landing.

Location tracking (also known as mobility tracking or mobility management) is the set of mechanisms by which location information is updated in response to mobility of a communication endpoint [7]. Many approaches such as Mobile IP try to hide the fact of changing access point by redirecting packets but maintaining the same IP address. There are several situations where knowledge of location could be beneficial for certain applications. Development of location aware services is a very active area of research in both cellular wireless and adhoc/sensor network communities.

It is therefore, necessary to manage the mobility of terminals in a cellular network for smooth operation of the real-time applications. Mobility tracking based on signal strength measurements is solved by treating it as on-line estimation in a nonlinear dynamic system. For example, Extended Kalman filter has been used to solve this problem in [8, 9].

Traditionally, in GSM type of network, the base-stations are fixed at a particular location. In this paper, we relax this assumption by assuming that the base-stations are free to move randomly and organize themselves arbitrarily; thus, the network's wireless topology may change rapidly and unpredictably.

This paper presents a use of robust extended Kalman filter (REKF) in the prediction of a mobile users arrival in the next cell, based on new theoretical results presented in [10, 11]. Our implementation with a single mobile-base station uses only the measurement from the closest neighboring station and hence improves the computational efficiency. Our second proposal further improves the prediction performance by using measurements from only two base stations which are fixed relative to the current cell. This eliminates the need to sample with six GSM base stations as demonstrated in [8] and hence considerably reduces the network traffic while improving the computational efficiency in using this algorithm. Further, in this paper we propose a much more realistic model in which vehicle acceleration may be any bounded function of time as opposed to the stochastic model given in [8] which is not realistic in practice as acceleration of a real vehicle cannot be represented by a Gaussian stochastic process. Moreover, our model incorporates significant uncertainty and measurement errors. Simulation results are provided to demonstrate the superiority of the proposed algorithm. Our work assumes availability of onboard GPS and acceleration of the wireless-basestaitons but not of the mobile terminals.

Besides the example scenarios given above, our work can be useful in tactical environments for accurate prediction of location of various objects and targets. Sensor networks can benefit from this work where a few powerful robot-based sensors (acting as base-stations) can roam around and collect data from small static (or mobile) sensor devices scattered in the environment.

The paper is organized as follows. Section 2 presents the related work with section 3 emphasizing the system dynamic model with the nonlinear measurement model. Section 4 states the theoretical background for the Robust Extended Kalman filter as a state estimator with reference to set valued state estimation ideas. Simulation details and results are given in section 3 with the conclusion in section 6.

2. RELATED WORK

Most of the recent work on location management in Adhoc network has been in sensor network area where the term used is *localization* (determining position of a sensor device in some co-ordinate system). Example of indoor localization are the Cricket project at MIT [12, 13], and work by Savvides et al. [14]. Bulusu et al. [15] provide a good overview of such work and their own scheme for outdoor localization for very small devices. However, requirements for localization for these small devices are different from the application scenarios that we have discussed. Work close to ours in the networking community have been mostly in the area of wireless cellular network (Robotics and military application may have some work using these techniques). We provide a brief overview of a few sample work.

The location management approach is two folds: Location update and location prediction. As a passive strategy, in location update, the system periodically records the current location of the mobile terminal in some database that it maintains. Location update algorithms can either be *static* or *dynamic* depending on whether the location updating is triggered based on network topology or users' call and mobility patterns. The location prediction is a dynamic strategy in which the system proactively estimates the mobile's location based on a user movement model.

Most of the recent studies have mainly focused on the update method [16, 17, 18], less attention has been given to the prediction side. Accurate prediction of a mobile terminal based on its previous location will improve the efficiency of location management task even from the update and systems perspective. The task of location management and resource reservation will become easy if user's movement pattern is known in advance. Even if the destination and possible trajectory may be known, a user may choose a different route while driving to same destination based on traffic congestion.

Tabbane [19] proposes that a mobile terminal's location can be derived from its quasi-deterministic mobility behavior and can be represented as a set of movements in a user profile. A pattern matching/recognition - based Mobile Motion Prediction (MMP) has been proposed as an enhancement on Tabbane's method [20]. Bhattacharya et al. [21] use information-theoretic approach to characterize the complexity of the mobility tracking problem in a cellular network. Shannon's entropy measure is identified as a basis for comparing user mobility models. By building and maintaining a dictionary of individual user's path updates, the proposed adaptive on-line algorithm can learn subscribers' profiles. These and several other similar schemes don't perform well when random factor is reintroduced or assumptions regarding rectilinear movement pattern etc., are removed.

Extended Kalman filter technique has been applied in [8, 22]. Yang et al. [23] have proposed application of sequential Monte Carlo (SMC) methodology to the problem of joint on-line mobility tracking and hard handoff detection. This uses computationally expensive Monte Carlo simulations to estimate the posterior distribution of the unknown states of the dynamic system while it is based on Markovian assumptions of mobile user dynamics with Gaussian sensory noise.

As it has been realized that further improvements can be achieved via efficient prediction, in this paper we propose using a Robust Extended Kalman Filter(REKF) as a state estimator in predicting mobile user's expected trajectory for efficient allocation of resources. These robust state estimation ideas emerged from the work of Savkin and Petersen [10]. It not only provides satisfactory results [24], but also eliminates the requirement of the knowledge or modelling of the user mobility pattern and measurement noise in comparison to standard Kalman filter implementation presented in [8]. In addition, our implementation only requires a single base station measurement/sampling (another base station for further improvements) although existing techniques need the network measurement with a minimum of three base stations [23, 19] while sampling with many more may be needed in obtaining the closest three.

3. MOBILE-BASESTATION AND MOBILE-USER DYNAMIC MODEL

The user mobility models found in literature vary from straight line motion assumption ([25, 26]) to acceleration modelled as Markov process with finite number of states ([8, 23]) with a time correlated random acceleration (semi-Markov). Our algorithm does not assume any such models for the mobile user and essentially considers as bounded yet unknown "noise" as well as the senor measurement noise of the base station. This ensures the robustness of the algorithm for a network which is inherently subjected to unknown and different forms of user mobility patterns and noise.

We use the terminology *Car* for a mobile-basestation in this paper (other mobile vehicles/robots fitted with a base-station would fit into the same category). Using basic kinematics, the dynamic model for the i^{th} car : Car_i and the mobile user to be used in this approach can be given in the two dimensional Cartesian coordinates as [27] :

$$\dot{x_i}(t) = \quad Ax_i(t) + B_1 u_i(t) + B_2 w(t) \tag{1}$$

where

$$A = \begin{bmatrix} \Theta & 0 \\ 0 & \Theta \end{bmatrix}, \quad B_1 = -B_2 = \begin{bmatrix} \Phi & 0 \\ 0 & \Phi \end{bmatrix}$$

with

$$\Theta = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, \quad \Phi = \begin{bmatrix} 0 \\ -1 \end{bmatrix}. \tag{2}$$

$x_i(t) = \begin{bmatrix} \mathrm{X}_i(t) & \dot{\mathrm{X}}_i(t) & \mathrm{Y}_i(t) & \dot{\mathrm{Y}}_i(t) \end{bmatrix}'$ is the dynamic state vector with $\mathrm{X}_i(t)$ and $\mathrm{Y}_i(t)$ representing the position of the user with respect to the base station(i^{th} car) at time t, and their first order derivatives $\dot{\mathrm{X}}(t)$ and $\dot{\mathrm{Y}}(t)$ representing the relative speed along the X and Y directions. In other words, if $x_M(t) = [x_M(t)\ \dot{x}_M(t)\ y_M(t)\ \dot{y}_M(t)]'$ represent the absolute state (position and velocity in order in the X and Y direction respectively) of the mobile user and $x^i_C(t) = \left[x^i_C(t)\ \dot{x}^i_C(t)\ y^i_C(t)\ \dot{y}^i_C(t)\right]'$ denote the absolute state of the i^{th} car in the same order, then $x_i(t) \triangleq x_M(t) - x^i_C(t)$. Furthermore, let $u_i(t)$ denote the two dimensional driving or acceleration command of the car from the respective accelerometer readings and $w(t)$ denote the unknown two-dimensional driving/acceleration command of the mobile user.

3.1 Measurement model

In cellular systems, the distance between the mobile and a known base station is practically observable. Such information is inherent in the forward link RSSI (received signal strength indication) of a reachable base station. Measured in decibels at the mobile station, RSSI can be modelled as a two fold effect : due to path loss and due to shadow fading [8]. Fast fading is neglected assuming that a low-pass filter is used to attenuate Rayleigh or Rician fade. Denoting the i^{th} car as $\mathrm{Car_i}$(figure 1), the RSSI from the $\mathrm{Car_i}$, $p_i(t)$ can be formulated as [28]

$$p_i(t) = p_{oi} - 10\varepsilon \log d_i(t) + v_i(t), \tag{3}$$

where p_{oi} is a constant determined by transmitted power, wavelength, and antenna gain of $\mathrm{Car_i}$. ε is a slope index(typically 2 for highways and 4 for microcells in the city), and $v_i(t)$ is the logarithm of the shadowing component, which is considered as an uncertainty in the measurement. $d_i(t)$ represents the distance between the mobile and base station of $\mathrm{Car_i}$, which can be further expressed in terms of the mobile's position with respect to the location of the i^{th} car i.e $(\mathrm{X}_i(t), \mathrm{Y}_i(t))$

$$d_i(t) = \left(\mathrm{X}_i(t)^2 + \mathrm{Y}_i(t)^2\right)^{1/2} \tag{4}$$

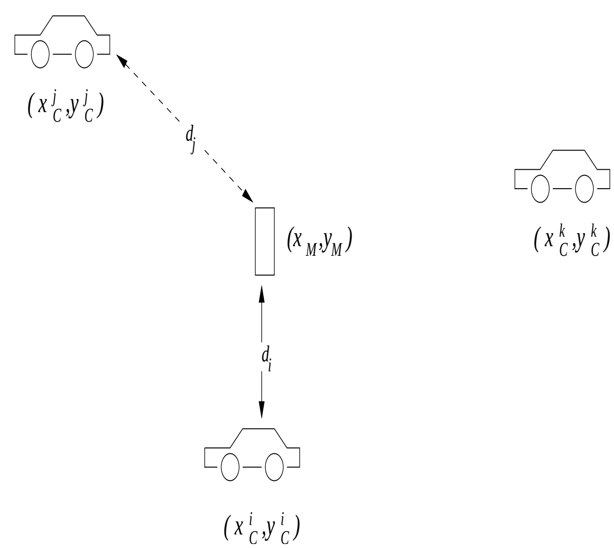

Figure 1: Network Geometry

In [8] three independent distance measurements are used to locate a moving user in two dimensional domain as GSM systems sample the forward link signal levels of six neighboring cells. Here, we propose a two fold implementation scheme. Our first implementation algorithm uses a single base station measurement that is closest to the user (i.e., highest value of the sampled six neighboring stations) as opposed to three. In our second implementation, further improvements can be made by using progressive measurement from two base stations. In this case we use the two closest cars. For the first implementation, the measurement equation is

$$y(t) = \min_{i \in \{1..K\}} p_i \tag{5}$$

with K denoting the number of cars in the network and for the second implementation, two measurements to form the observation vector

$$y(t) = \left[\begin{array}{c} p_o^1(t) \\ p_o^2(t) \end{array} \right], \quad \text{with}$$
$$p_o^1 = \min_{i \in \{1..K\}} p_i \quad \text{and} \quad p_o^2 = \min_{j \in \{1..K \setminus i\}} p_j,$$

are chosen progressively as the user moves in the coverage area. We use measurements from the two closest base stations and therefore the measurement equation (from equation 3) is in the form of

$$y(t) = C(x(t)) + v(t) \tag{6}$$

where $v(t) = [v_i(t)\ v_j(t)]'$ with

$$C(x_i(t)) = \left[\begin{array}{c} p_{oi} - 10\varepsilon \log\left(\mathrm{X}_i(t)^2 + \mathrm{Y}_i(t)^2\right) \\ p_{oi} - 10\varepsilon \log\left(\mathrm{X}_i(t) + x_C^i(t) - x_C^j(t)\right)^2 \\ + \left(\mathrm{Y}_i(t) + y_C^i(t) - y_C^j(t)\right)^2 \end{array} \right] \tag{7}$$

corresponding the noise free portion of the RSSI (equation 3) for two vehicles with i corresponds to the nearest car to the mobile user and j corresponds to the car 2^{nd} nearest to the mobile user.

4. SET-VALUE STATE ESTIMATION WITH A NON-LINEAR SIGNAL MODEL

The measurement equation emerging from equation 3 is nonlinear and therefore, we consider a nonlinear uncertain system of the form

$$\begin{aligned} \dot{x} &= A(x,u) + B_2 w \\ z &= K(x,u) \\ y &= C(x) + v, \end{aligned} \tag{8}$$

as a general form of the system given by equation 1 with measurement equation in the form of equation 6, and defined on the finite time interval $[0,s]$. Here, $x(t) \in \mathbb{R}^n$ denotes the *state* of the system, $y(t) \in \mathbb{R}^l$ is the *measured output* and $z(t) \in \mathbb{R}^q$ is the *uncertainty output.* The uncertainty inputs are $w(t) \in \mathbb{R}^p$ and $v(t) \in \mathbb{R}^l$. Also, $u(t) \in \mathbb{R}^m$ is the known *control input.* We assume that all of the functions appearing in (8) are with continuous and bounded partial derivatives. Additionally, we assume that $K(x,u)$ is bounded. This was assumed to simplify the mathematical derivations and can be removed in practice [11, 29]. The matrix B_2 is assumed to be independent of x, and is of full rank.

The uncertainty in the system is defined by the following *nonlinear integral constraint* [10, 11, 30, 31, 32] :

$$\Phi\left(x(0)\right) + \int_0^s L_1\left(w(t), v(t)\right) dt \le d + \int_0^s L_2\left(z(t)\right) dt, \tag{9}$$

where $d \ge 0$ is a positive real number. Here, Φ, L_1 and L_2 are bounded non-negative functions with continuous partial derivatives satisfying growth conditions of the type

$$\|\phi(x) - \phi(x')\| \quad \le \quad \beta\left(1 + \|x\| + \|x'\|\right)\|x - x'\| \tag{10}$$

where $\|\cdot\|$ is the euclidian norm with $\beta > 0$, and $\phi = \Phi, L_1, L_2$. Uncertainty inputs $w(\cdot), v(\cdot)$ satisfying this condition are called *admissible uncertainties.* We consider the problem of characterizing the set of all possible states $\mathcal{X}_s$ of the system (8) at time $s \ge 0$ which are consistent with a given control input $u^0(\cdot)$ and a given output path $y^0(\cdot)$; i.e., $x \in \mathcal{X}_s$ if and only if there exists admissible uncertainties such that if $u^0(t)$ is the control input and $x(\cdot)$ and $y(\cdot)$ are resulting trajectories, then $x(s) = x$ and $y(t) = y^0(t)$, for all $0 \le t \le s$.

4.1 The State Estimator

The state estimation set $\mathcal{X}_s$, which is a solution to the system 1 with the uncertainty bound given by equation 9 is characterized in terms of level sets of the solution $V(x,s)$ of the Partial Differential Equation (PDE)

$$\begin{aligned} \frac{\partial}{\partial t}V + \quad & \max_{w \in \mathbb{R}^m} \{\nabla_x V.\left(A(x,u^0) + B_2 w\right) \\ & -L_1\left(w, y^0 - C(x)\right) + L_2\left(K(x,u^0)\right)\} \quad = 0 \\ & V(\cdot, 0) = \Phi. \end{aligned} \tag{11}$$

The PDE (11) can be viewed as a filter, taking observations $u^0(t), y^0(t)$, $0 \le t \le s$ and producing the set $\mathcal{X}_s$ as a output. The state of this filter is the function $V(\cdot, s)$; thus V is an information state for the state estimation problem.

THEOREM 1. *Assume the uncertain system (8), (9) satisfies the assumptions given above. Then the corresponding set of possible states is given by*

$$\mathcal{X}_s = \{x \in \mathbb{R}^n : V(x,s) \le d\}, \tag{12}$$

where $V(x,t)$ is the unique viscosity solution of equation (11) in $C\left(\mathbb{R}^n \times [0,s]\right)$.

PROOF. see [11]. □

4.2 A Robust Extended Kalman Filter

As the complete solution to the PDE (11) is hard to derive, we use an approximation which leads to a Kalman filter like characterization of the set $\mathcal{X}_s$. Petersen and Savkin in [11] presented this as a Extended Kalman filter version of the solution to the Set Value State Estimation problem for a linear plant with the uncertainty described by an Integral Quadratic Constraint (IQC). This IQC is also presented as a special case of equation 9. We consider uncertain system described by (8) and an integral quadratic constraint of the form

$$\begin{aligned} & \left(x(0) - x_0\right)' X_0 \left(x(0) - x_0\right) \\ & + \frac{1}{2}\int_0^s \left(w(t)' Q(t) w(t)\right) + v(t)' R(t) v(t) dt \\ & \qquad \le d + \frac{1}{2}\int_0^s z(t)' z(t) dt, \end{aligned} \tag{13}$$

where $N > 0, Q > 0$ and $R > 0$. For the system (8), (13), the PDE (11) can be written as

$$\begin{aligned} & \tfrac{\partial}{\partial t}V + \nabla_x V.A(x,u^0) + \tfrac{1}{2}\nabla_x V B_2 Q^{-1} B_2' \nabla_x V' \\ & -\tfrac{1}{2}\left(y^0 - C(x)\right)' R\left(y^0 - C(x)\right) \\ & +\tfrac{1}{2}K(x,u^0)' K(x,u^0) = 0, \\ & V(x,0) = \left(x - x_0\right)' N\left(x - x_0\right). \end{aligned} \tag{14}$$

Considering a function $\hat{x}(t)$ defined as

$$\hat{x}(t) \triangleq \arg\min_x V(x,t),$$

and the following equations (15),(16) and (17), define our approximate solution to the PDE (14) :

$$\dot{\tilde{x}}(t) = A\left(\tilde{x}(t), u^0\right) + X^{-1}[\nabla_x C\left(\tilde{x}(t)\right)' R\left(y^0 - C\left(\tilde{x}(t)\right)\right)$$
$$+\nabla_x K\left(\tilde{x}(t), u^0\right)' K\left(\tilde{x}(t), u^0\right)],$$
$$\tilde{x}(t) = x_0. \quad (15)$$

$X(t)$ is defined as the solution to the Riccati Differential Equation (RDE)

$$\dot{X} + \nabla_x A\left(\tilde{x}, u^0\right)' X + X\nabla_x A\left(\tilde{x}, u^0\right)$$
$$+XB_2Q^{-1}B_2'X - \nabla_x C(\tilde{x})' R\nabla_x C(\tilde{x})$$
$$+\nabla_x K\left(\tilde{x}, u^0\right)' \nabla_x K\left(\tilde{x}, u^0\right) = 0,$$
$$X(0) = N. \quad (16)$$

and

$$\phi(t) \triangleq \tfrac{1}{2}\int_0^t [\left(y^0 - C(\tilde{x})\right)' R\left(y^0 - C(\tilde{x})\right)$$
$$-K\left(\tilde{x}, u^0\right)' K\left(\tilde{x}, u^0\right)]d\tau. \quad (17)$$

The function $V(x,t)$ was approximated by a function of the form

$$\tilde{V}(x,t) = \frac{1}{2}\left(x - \tilde{x}(t)\right)' X(t)\left(x - \tilde{x}(t)\right) + \phi(t).$$

Hence, it follows from Theorem 1 that an approximate formula for the set $\mathcal{X}_s$ is given by

$$\tilde{\mathcal{X}_s} = \left\{x \in \mathbb{R}^n : \frac{1}{2}\left(x - \tilde{x}(s)\right)' X(s)\left(x - \tilde{x}(s)\right) \leq d - \phi(s)\right\}$$

This amounts to the so called Robust Extended Kalman Filter generalization presented in [11].

In the application of REKF in the Adhoc network, the i^{th} system (vehicle - Car_i and the mobile user) tracking the mobile user during a corresponding time interval is represented by the nonlinear uncertain system in (8) together with the following Integral Quadratic Constraint (IQC)(from equation 13) :

$$\left(x(0) - x_0\right)' N_i\left(x(0) - x_0\right)$$
$$+\frac{1}{2}\int_0^s \left(w(t)' Q_i(t)w(t)\right) + v(t)' R_i(t)v(t)dt$$
$$\leq d + \frac{1}{2}\int_0^s z(t)' z(t)dt. \quad (18)$$

Here $Q_i > 0, R_i > 0$ and $N_i > 0$ with $i \in \{1,2,3\}$ are the weighting matrices for each system i, while the initial state (x_0), is the estimated state of respective systems in the acquiring handover time. This initial state is essentially derived from the terminal state of the previous system together with other data available in the network(i.e., vehicle position available from GPS and speed) to be used as the initial state for the next system taking over the tracking. With an uncertainty relationship of the form of (18), the inherent measurement noise(see equation 6), unknown mobile user acceleration/driving command and the uncertainty in the initial condition are considered as bounded deterministic uncertain inputs. In particular, the measurement equation with the standard norm bounded uncertainty can be written as (equation 6)

$$y = C(x) + \delta C(x) + v_0$$

where $|\delta| \leq \xi$ with ξ, a constant indicating the upper bound of the norm bounded portion of the noise. By choosing $z = \xi C(x)$ and $\nu = \delta C(x)$,

$$\int_0^T |\nu|dt \leq \int_0^T z'zdt.$$

Considering v_0 and the corresponding uncertainty in w as w_0 satisfying the bound in the form of

$$\Phi\left(x(0)\right) + \int_0^T \left[w_0(t)'Qw_0(t) + v_0(t)'Rv_0(t)\right]dt \leq d,$$

it is clear that this uncertain system leads to the satisfaction of condition in inequality 9 and hence 13 (see [11]). This more realistic approach removes any noise model assumptions in our algorithm development and guarantees the robustness.

5. SIMULATION

To examine the application and performance of the Robust Extended Kalman Filter in an Adhoc type network, simple simulations are carried out for a mobile-user in a three car coverage area. The network is assumed to have location and acceleration information of the mobile base stations via GPS and accelerometer reading while no such information is available with respect to the mobile user of an arbitrary kind. We simulated the two fold scenarios we introduced earlier.

1. Measurement from the closest base station i.e., the largest measurement from the three neighboring base stations. The tracking is performed by the closest car.

2. Two base stations which are closest to the mobile terminal are used for measurement. The tracking is performed by the closest car however the second closest car is also performing measurements.

The simulated service area contains three cars for illustrative purposes and can obviously be scaled for as many mobile-basetstations and users as required. Identical parameters (table 1) were used for our simulations in each case for comparison purposes. The simulation parameters commonly known as tuning parameters (N_i, Q_i and R_i) are relative weights associated with initial conditions, unknown maneuver of the mobile user and the sensor noise respectively for each systems of Car_i and the mobile user(see equation 18). Therefore by changing these parameters, we increase/decrease the relative tolerance of the systems i for the respective characteristic.

In the simulation of the dynamical system, we choose the functions given in table 2 for arbitrary car accelerations(u_i's) and unknown mobile user acceleration(w). The arbitrary user mobility pattern where ϕ_1, and ϕ_2 being uniform random distributions in the interval $[0 \ \ 0.2A_{max}]$. We use a uniform random distribution in the interval $[0 \ \ 0.05A_{max}]$ for the measurement noise with $\xi = 0.05$. The equation for the state estimation and the corresponding Riccati Differential equation obtained from equation 15 and 16 are as follows:

Parameter	Value	Comments
p_{oi}	20w	Base station transmission power
$\{N_1, N_2, N_3\}$	$\{0.1, 0.1, 0.0.095\} \times I_4$	Weighting on the initial viscosity solution
$\{Q_1, Q_2, Q_3\}$	$\{5, 5, 1\} \times 10^{-3} I_2$	Weighting on the uncertainty in the user driving command
$\{R_1, R_2, R_3\}$	$\{6, 7, 5\} \times 10^3$ I_1 for scenario 1 and I_2 for scenario 2	Weighting on the measurement noise
T	$70mins$	Simulation time
A_{max}	$3.3m/s^2$	Amplitude of the user driving command
Ts	0.6s	Sampling interval
$x_1(0)$	$[0\ 0\ \cos(10)\ \sin(10)]'$ $\times$500-30km/hr speed at 10^o to the X axis	Initial state wrt. the 1^{st} car
$x_2(0)$	[150000833.33 cos(140) 833.33 sin(140)]'-50km/hr at 140^o to the X axis	Initial state wrt. the 2^{st} car
$x_3(0)$	[8000 20000 166.7 cos(240) 166.7 sin(240)]'-10km/hr at 240^o to the X axis	Initial state wrt. the 3^{rd} car

Table 1: Simulation parameters.

Vehicle	Car Acceleration
1	$A_{max}[-3\sin(0.2t) + 0.2\phi_1$ $0.9\cos(0.05 * t) + 0.2\phi_2]'$
2	$1.6A_{max}[3\sin(0.2t) + 0.2\phi_1$ $-2.0\cos(0.09t) + 0.2\phi_1]'$
3	$A_{max}[4\sin(0.3t) + 0.2\phi_1$ $-3\cos(0.1 * t) + 0.2\phi_2]'$
Mobile user	$A_{max}[-\cos(0.1t) + 0.2\phi_1$ $1\sin(0.1t) + 0.2\phi_2]'$

Table 2: Acceleration of dynamical entities

$$
\begin{aligned}
\dot{\tilde{x}}(t) &= A\tilde{x}(t) + B_1 u_i(t) \\
&\quad + X^{-1}(t)[\beta^1\tilde{x}(t)' R_i\left(y(t) - \beta\left(\tilde{x}(t)\right)\right) + \xi^2\beta^1\tilde{x}(t)'\beta^1\tilde{x}(t)], \\
&\qquad \tilde{x}(t) = x_0. \\
\dot{X} &+ A'X + XA + XB_2Q_i^{-1}B_2'X - \\
&\quad \beta^1\tilde{x}(t)'R_i\beta^1\tilde{x}(t) + \xi^2\beta^1\tilde{x}(t)'\beta^1\tilde{x}(t) = 0, \quad X(0) = N_i.
\end{aligned}
$$

where for the case of single base station measurement

$$\beta(x_i) = p_i$$

with i corresponding to the closest base station, and for the case of two base station measurement

$$\beta(x) = C(x)$$

as shown in equation 7. Also here

$$\beta^1(x) = \nabla_x \beta(x), \tag{19}$$

x_0 is the last state before the handover.

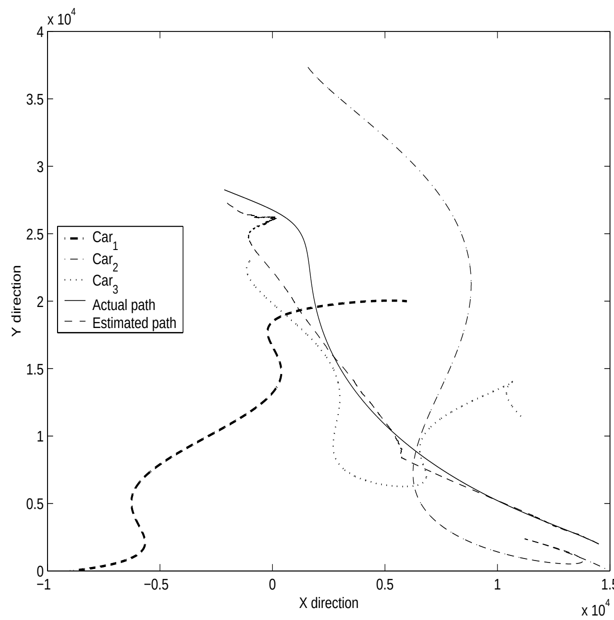

Figure 2: Trajectories of the cars and the mobile user for the case of single base station measuring

Time Period	Closest Car
[0 18] min	Car_2
[18 31.2] min	Car_3
[31.2 67.9] min	Car_1
[67.9 70] min	Car_2

Table 3: Cars tracking the mobile user during the time period (single base station measuring)

5.1 Discussion of results

The simulation of mobility modelling and trajectory tracking of a mobile user purely with signal strength measurements by three cars and a arbitrary mobile user in a 15×40km sub-urban area, were performed successfully in a two fold scenario. We have restricted the number of base stations to a minimum to ensure the clarity and simplicity in demonstration and can obviously be scaled to as many base stations as required. In the first scenario, a single car (the closest car) is measuring the forward link signal in the GSM system and tracks the mobile user's location and predicts the velocity as shown in figure 2 and 3. The respective handover time and corresponding vehicles are given in table 3. The second implementation we propose ensures further improvements by involving the additional second closest car

Time Period	Closest Car	2^{nd} Closest Car
[0 18] min	Car_2	Car_1
[18 31.1] min	Car_3	Car_2
[31.1 61.3] min	Car_1	Car_3
[61.3 70] min	Car_2	Car_1

Table 4: Cars tracking the mobile user during the time period (dual base station measuring)

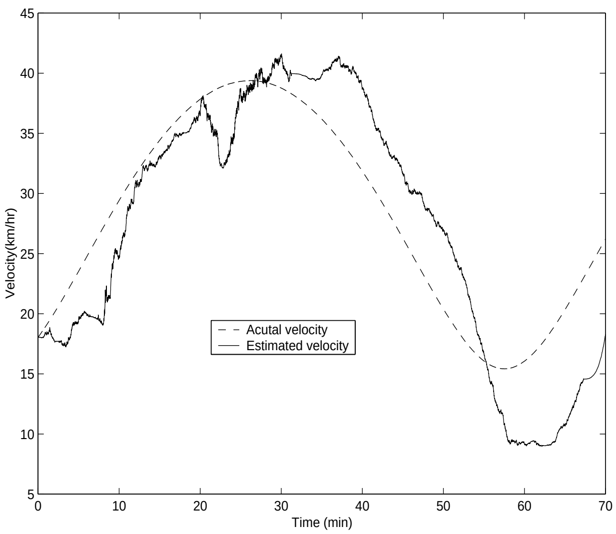

Figure 3: Actual and Estimated velocities of the mobile user for the case of single base station measuring

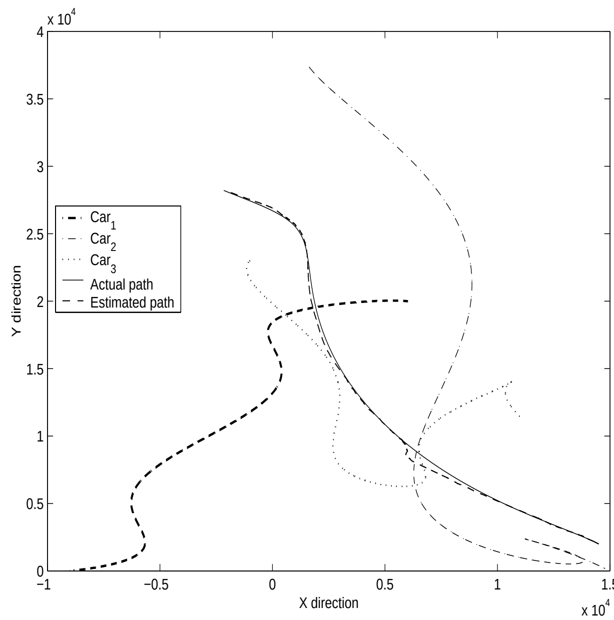

Figure 4: Trajectories of the cars and the mobile user for the case of dual base station measuring

for measuring the forward link signal. Using identical parameters as for the case of single base station measuring, our second scenario produced improved tacking of position and velocity of the mobile user. The significant improvement in location estimation is shown in figure 4 and the performance comparison/improvement in location estimation of the two scenarios is shown in figure 6. Compared to the estimated velocity in the first case (figure 3), figure 5 shows the improvement in velocity estimation. The tracking performed by the closest car and the forward link measuring by the two closest cars are shown in table 4 with the corresponding tracking/measuring and handover times.

6. CONCLUSION

We have provided a scheme for mobility estimation and prediction for an adhoc network consisting of mobile basestations and mobile-users. To best of our knowledge no other study has been done for such a network. The desire was to develop an effective, robust and easily implementable algorithm with less burden on the system resources while effectively using the readily available mobile base stations (such as cars fitted with base stations). We proposed use of a Robust Extended Kalman Filter based state estimation algorithm. It is evident from our research, a single mobile base station can successfully be used for tracking the mobile user in the wireless network (existing schemes need RSSI measurements from at least three base stations). Further improvements for the overall system performance can be achieved by our second proposed technique by using the next closest car for measurement purposes. Emerging from a recent theoretical development, REKF can successfully be used in the prediction of a mobile user's location in a wireless ad hoc network with tracker and measurers switching appropriately. As our implementation with a single base station uses only the measurement from the closest neighboring station, the computational efficiency of the overall network is significantly improved. Also our second proposal further improves the system performance by using measurements from only two base stations which are closest to the mobile user eliminating the need to sample with more (six) base stations as in PCS networks. This considerably reduces the network traffic while improving the computational efficiency. Our algorithm is clearly computationally efficient in comparison to extended Kalman filter implementation provided in many PCS networks and it can be implemented within the mobile user rather than in the basestation in order to reduce the signalling traffic. Most existing techniques use algorithm based on Gaussian noise models, semi-Markov models or extremely computationally expensive Monte Carlo trail and are therefore dependant on particular noise model, hence not optimal or robust for different noise models. In this work, as no assumptions were made on the measurement noise and uncertain user acceleration component. This ensures robustness of this algorithm is ensured. Our future work will consider extending this work to outdoor localization of small sensor devices.

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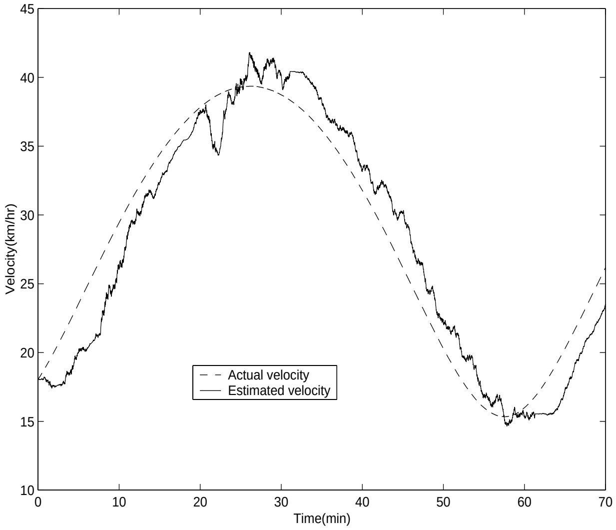

Figure 5: Actual and Estimated velocities of the mobile user for the case of dual base station measuring

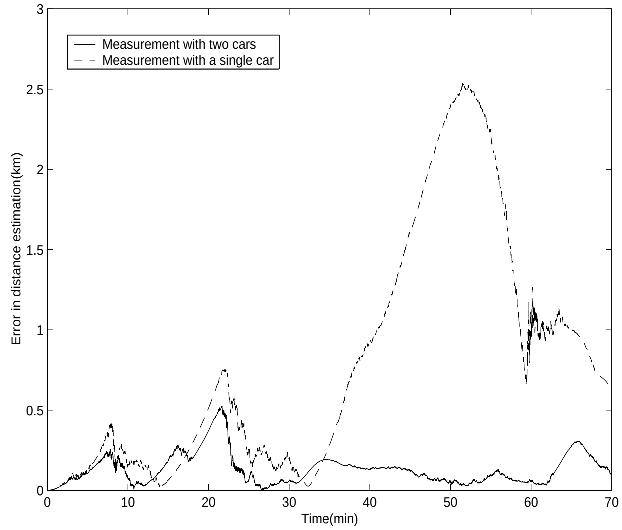

Figure 6: Error in Location estimation for single and dual car measurement

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