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Eighteenth Annual Signal and Imaging Science Workshop, Lawrence Livermore National Laboratory Center for Advanced Signal and Imaging Sciences (CASIS), May 21, 2014

Mobility Modeling and Estimation for Delay Tolerant Unmanned Ground Vehicle networks

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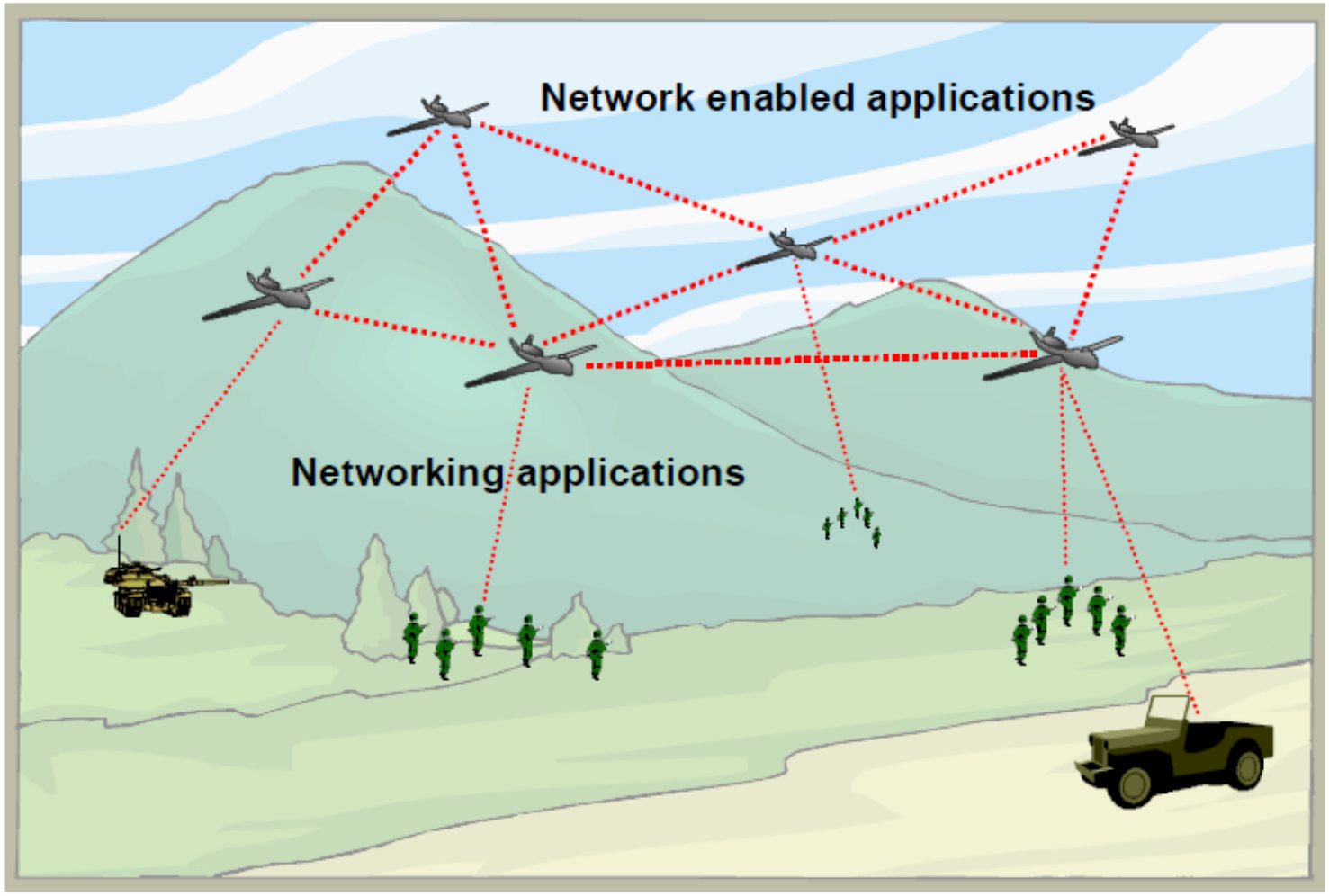
Grace Clark, Ph.D., IEEE Fellow, has a consulting business, Grace A. Clark, Ph.D., Consulting. From 2010-2012, she was a Visiting Research Professor in the Center for Cyber Warfare at the Naval Postgraduate School (NPS), Monterey, CA, on Professional Research and Teaching Leave from the Lawrence Livermore National Laboratory (LLNL), Livermore, CA. After more than 30 years at LLNL, she retired from LLNL in 2013 to run her consulting business. She earned BSEE and MSEE degrees from the Purdue University EE Honors Program and the Ph.D. ECE degree from the U. of California Santa Barbara. Her technical expertise is in statistical signal/image processing, estimation/detection, pattern recognition/machine learning, sensor fusion, communication and control. Dr. Clark has contributed more than 220 publications in the areas of acoustics, electro-magnetics and particle physics. Dr. Clark is a member of the ASA Technical Council on Signal Processing in Acoustics, as well as IEEE, SEG (Society of Exploration Geophysicists), Eta Kappa Nu and Sigma Xi.

Agenda

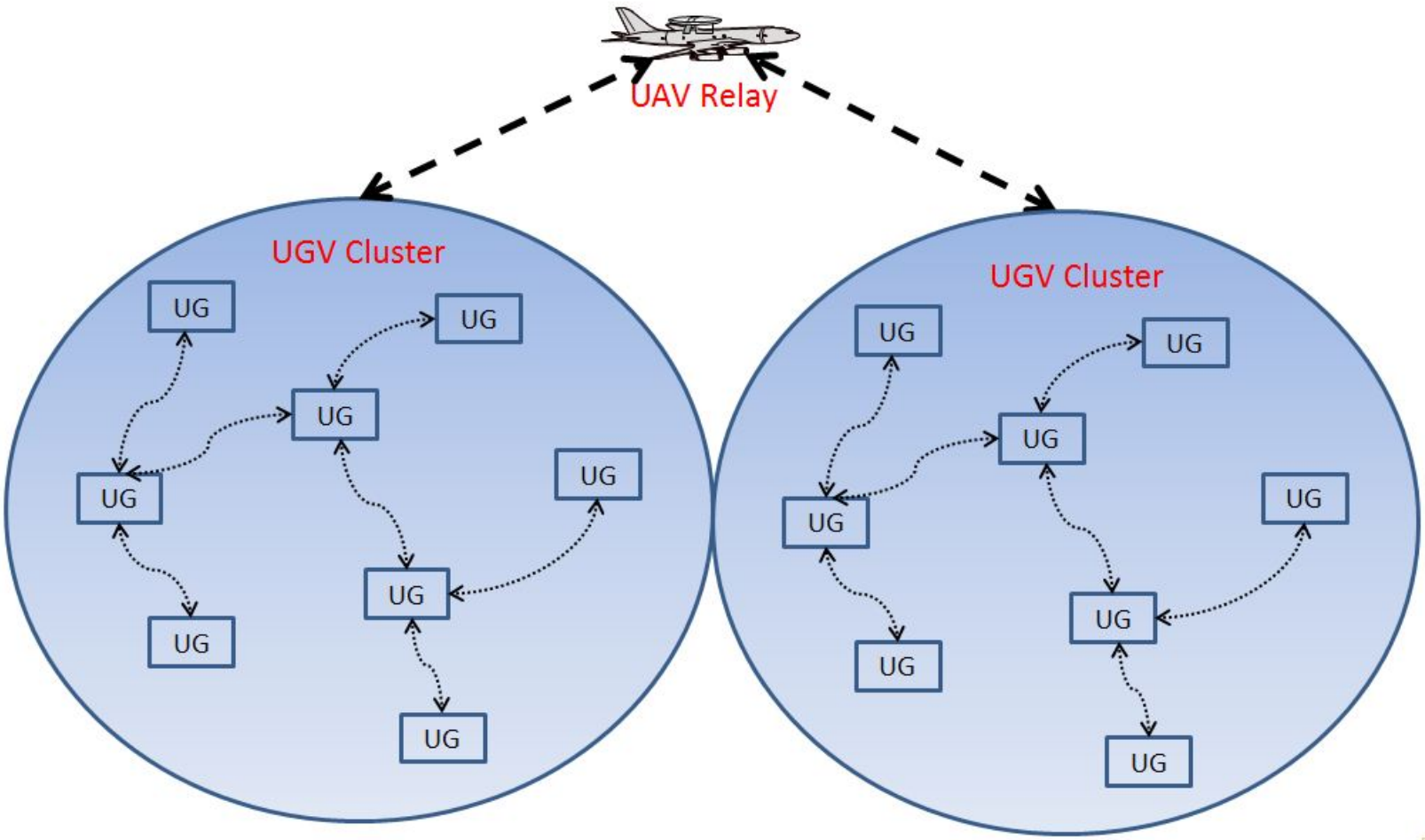
- Introduction/Problem Definition
- Previous Literature
- A Stochastic Mobility Model in the General Spatial Grid Setting
- The Extended Kalman Filter for Mobility Estimation
- Estimation Performance Measures
- Simulation Experiment and Performance Measurement
- Conclusions and Future Work

Our Focus is on Heterogeneous Wireless Mobile Ad-Hoc Networks (MANET's)



- Mobile Users ➔ UGV's, Vehicles, Ground Troops, etc.
- Delay Tolerant Networks (DTN's)

The Operational Setting Has a UAV Relay and Clusters of UGV Nodes



We Focus on Delay Tolerant Networks (DTN's)

- A UGV network operates as an intermediately connected mobile ad hoc network, otherwise known as a Delay Tolerant Network (DTN)
- A UGV-DTN is dynamic
- Path planning protocol must react to individual UGV movements (mobility)
- Knowledge of UGV mobility requires estimating UGV dynamic position, velocity and acceleration

Path Planning and Routing Require Mobility Estimation

- Mobility Estimation:

  We must d*evelop set of mobility algorithms that will achieve realistic estimates of the individual UGV nodes within the DTN*

- Path Planning

  We must develop a path planning strategy using the mobility estimation results as inputs to achieve cooperation among individual UGV nodes for routing

Problem Statement

The purpose of this work is to create a foundational algorithm for mobility estimation that can be coupled with a cooperative communication algorithm to provide a basis for real time cooperative planning in UGV-DTN's

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Brief Literature Review

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Mobility Modeling and Estimation Algorithm Design Involves Several Key Considerations

Purpose in UGV-DTN

- Produce estimates of position over time, and sometimes velocity and acceleration over time

Key Attributes

1) The operational mission setting and physical constraints
2) The set of available sensor measurements or observations
3) An appropriate physics model
4) An appropriate performance index or set of performance indices
5) An appropriate estimation/tracking algorithm or set of algorithms

The Operational Mission Setting is Key to the Technical Approach

- ***Constrained Grid Of Spatial Cells***

  - Movement within predefined grid with landmarks (such as college campus)

  - Wireless access point for movement measurement, storage and mobility estimation

  - *Not adequate for our operational mission(s)*

- ***Ad Hoc General Spatial Grid***

  – Operate wherever one is deployed, undefined or general spatial grid

  – RSSI signals from known base stations

  – *Appropriate for our operational missions*

Approaches Taken in Previous Networking Literature

- ***Authors Propose a New Mobility Estimation Algorithm***
  - Based on constrained spatial grid of cells and Markov-class models (Hidden Markov Models, etc.) and
  - Coupled with a standard routing protocol such as Ad Hoc On Demand Distance Vector (AODV) or Dynamic Source Routing (DSR), both on NS2 software
- ***Authors Propose a New Routing Protocol***
  - Coupled with standard mobility estimation model like random walk and random waypoint, also in NS2 software

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A Stochastic Mobility Model in the General Spatial Grid Setting

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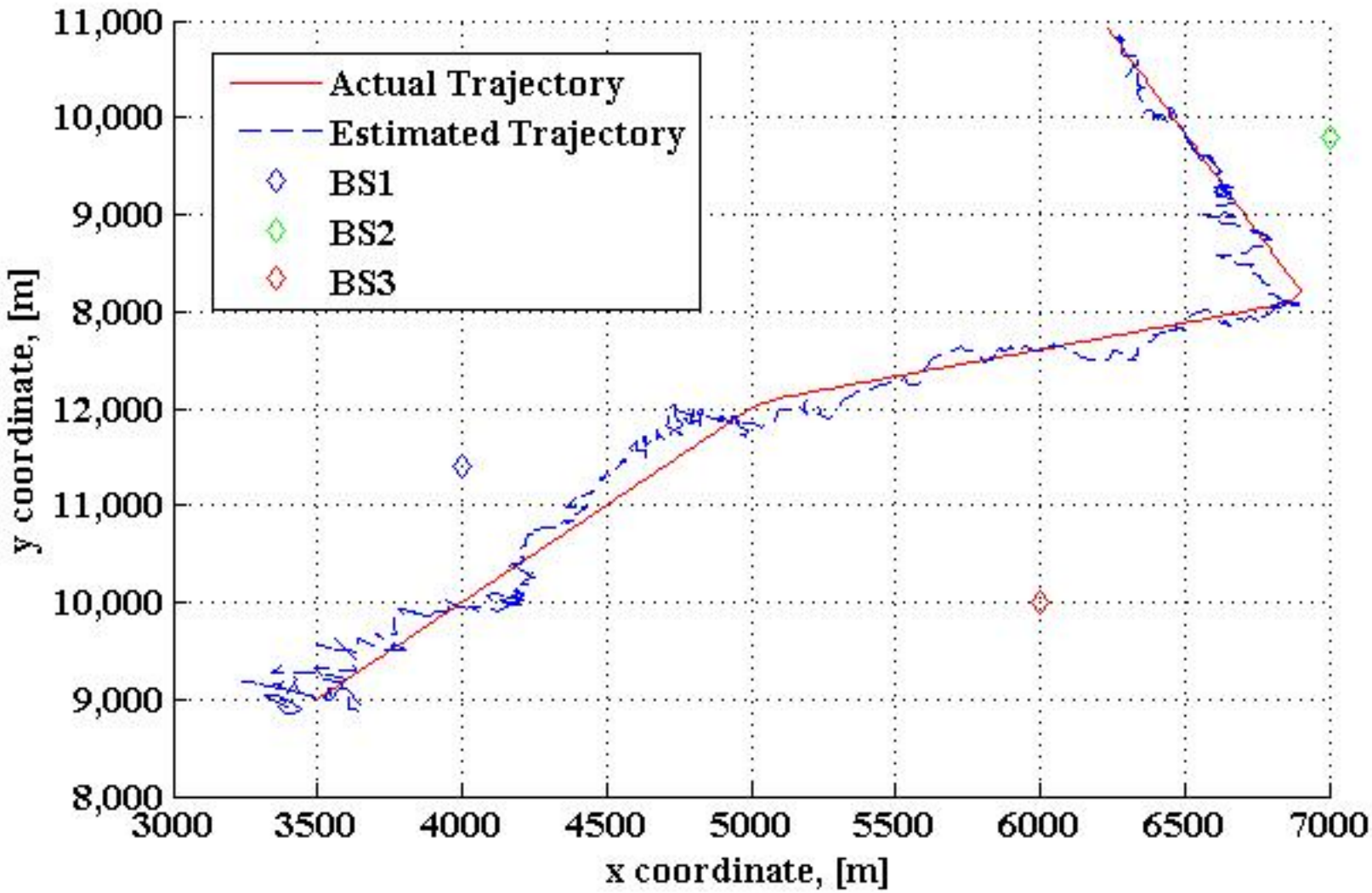
We Use a General 2D Spatial Grid Setting, Model-Based Signal Processing and a New Routing Protocol

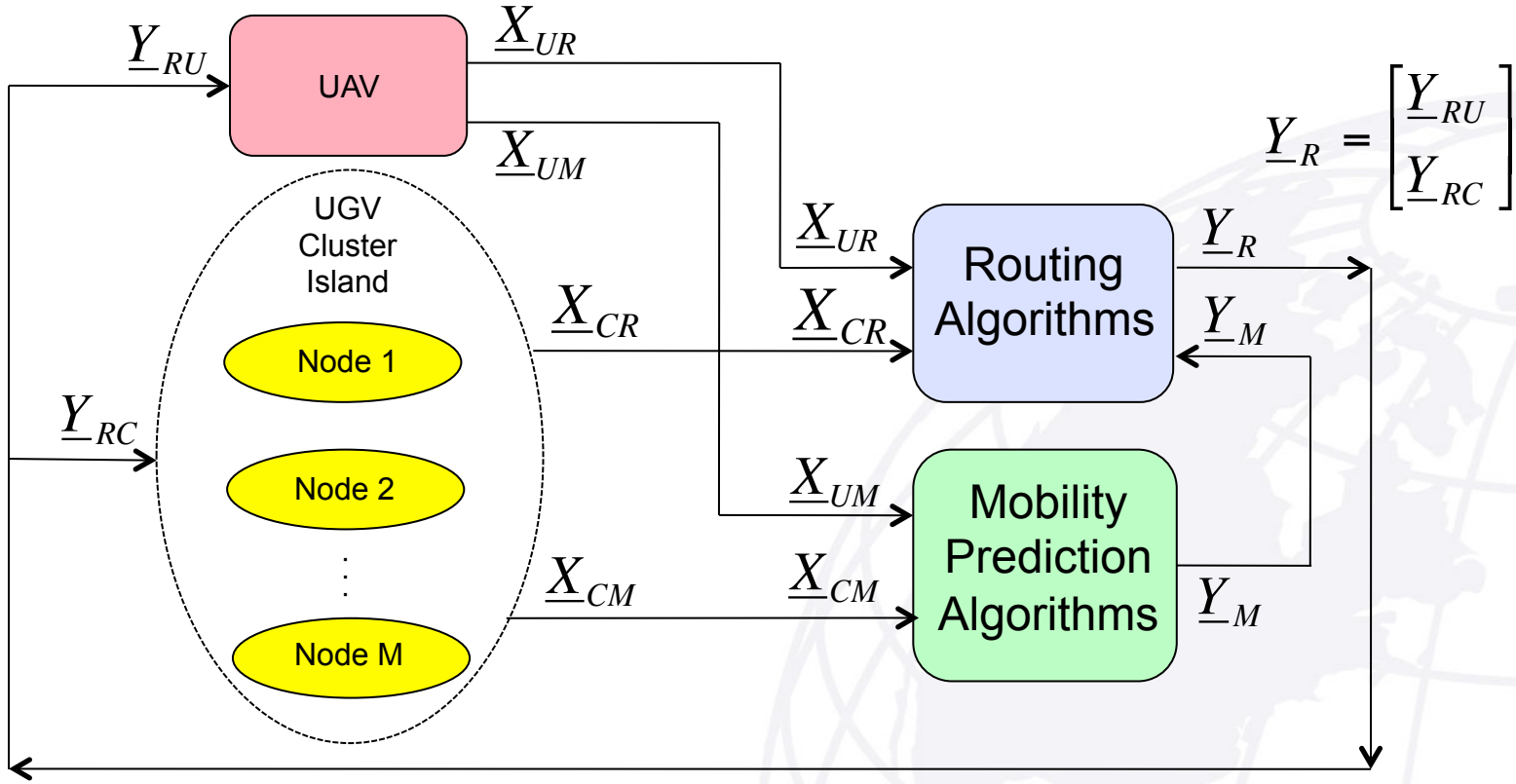
- Algorithms for both mobility estimation and the routing protocol that are new to the networking literature
- Our mobility estimation approach uses:
  - A general two-dimensional spatial grid setting
  - A dynamic Gauss-Markov state space mobility model
  - A first-order semi-Markov model for the command (input) function
  - Received signal strength indicator (RSSI) signals for the measurements
- The use of model-based signal processing and control techniques for mobility estimation in an ad hoc network is new to the networking literature

We Use a 2D General Spatial Grid Setting: *Preview Shown Below*

Note the Three Base Stations (Transmitters)



UAV and UGV Information Flow



$$\underline{X}_U = \text{Measurement Vector from UAV} = \begin{bmatrix} \underline{X}_{UR} \\ \underline{X}_{UM} \end{bmatrix} = \begin{bmatrix} \text{Measurements Needed for Routing} \\ \text{Measurements Needed for Mobility} \end{bmatrix}$$

$$\underline{X}_C = \text{Measurement Vector from Cluster} = \begin{bmatrix} \underline{X}_{CR} \\ \underline{X}_{CM} \end{bmatrix} = \begin{bmatrix} \text{Measurements Needed for Routing} \\ \text{Measurements Needed for Mobility} \end{bmatrix}$$

A Linear Discrete-Time Gauss-Markov Model is Used for the States of the Node

Linear Gauss-Markov Model for State of the Mobile Node

$$\underline{x}_k = A(T,\alpha)\,\underline{x}_{k-1} + B_u(T)\,\underline{u}_k + B_w(T)\,\underline{w}_k$$

- $\underline{x}_k = \left[x_k, \dot{x}_k, \ddot{x}_k, y_k, \dot{y}_k, \ddot{y}_k\right]^T$ denotes the state of the mobile node at time step k
- $\underline{u}_k = \left[u_{x,k}, u_{y,k}\right]^T$ denotes a realistic motion discrete-time command process
- $\underline{w}_k = \left[w_{x,k}, w_{y,k}\right]^T$ denotes a process noise, where $\underline{w}_k \sim N[0, R_w^2]$

T = The temporal sampling period in seconds

α = Reciprocal of the random acceleration time constant

- Gauss-Markov state space model modified to include a discrete semi-Markov type model (See next slide(s))
- The Jacobian matrix of the measurement vector is derived for use in the Kalman Filter (See subsequent slide)

A (6 x1) Discrete-Time Gauss-Markov State Space Model is Used for the States

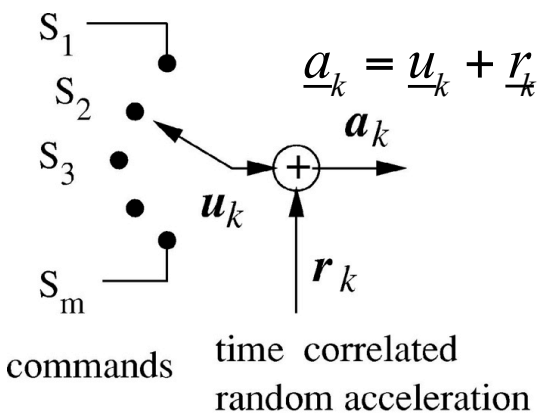
$$\underline{x}_k = A(T,\alpha)\underline{x}_{k-1} + B_u(T)\underline{u}_k + B_w(T)\underline{w}_k =$$

$$\begin{bmatrix} x_k \\ \dot{x}_k \\ \ddot{x}_k \\ y_k \\ \dot{y}_k \\ \ddot{y}_k \end{bmatrix} = \begin{pmatrix} 1 & T & \frac{T^2}{2} & 0 & 0 & 0 \\ 0 & 1 & T & 0 & 0 & 0 \\ 0 & 0 & \alpha & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & T & \frac{T^2}{2} \\ 0 & 0 & 0 & 0 & 1 & T \\ 0 & 0 & 0 & 0 & 0 & \alpha \end{pmatrix} \begin{bmatrix} x_{k-1} \\ \dot{x}_{k-1} \\ \ddot{x}_{k-1} \\ y_{k-1} \\ \dot{y}_{k-1} \\ \ddot{y}_{k-1} \end{bmatrix} + \begin{pmatrix} \frac{T^2}{2} & 0 \\ T & 0 \\ 0 & 0 \\ 0 & \frac{T^2}{2} \\ 0 & T \\ 0 & 0 \end{pmatrix} \begin{bmatrix} u_{x,k} \\ u_{y,k} \end{bmatrix} + \begin{pmatrix} \frac{T^2}{2} & 0 \\ T & 0 \\ 1 & 0 \\ 0 & \frac{T^2}{2} \\ 0 & T \\ 0 & 1 \end{pmatrix} \begin{bmatrix} w_{x,k} \\ w_{y,k} \end{bmatrix}$$

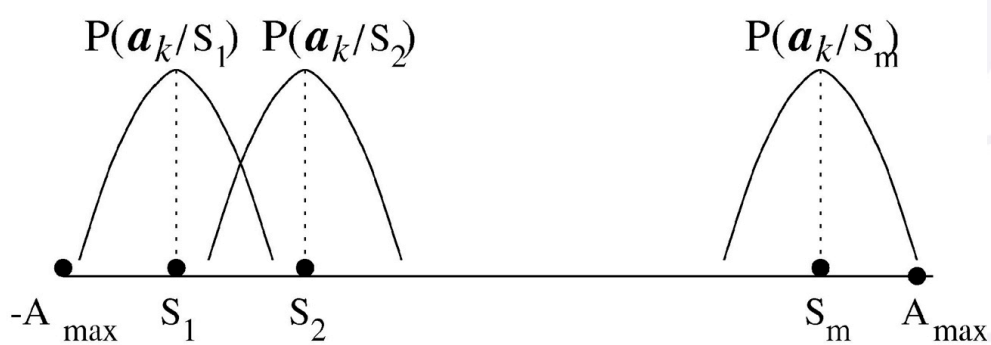
A (2 x 1) Discrete Semi-Markov Model is Used for the Command Input Signal

Aspects to Consider

- Realistic motion includes both continuous and discontinuous motion
- A mobile node is likely to change acceleration unexpectedly (i.e., turns)
- Acceleration is likely to be correlated over time, due to momentum



(a)



(b)

$$\underline{r}_{k+1} = -\alpha \underline{r}_k + \underline{w}_k$$

$$R_{rr}(\tau) = E\{\underline{r}(t)\underline{r}^T(t+\tau)\} = \sigma_m^2 e^{-\alpha|\tau|} I, \quad \alpha \geq 0$$

$$\underline{r}_{k+1} = -\alpha \underline{r}_k + \underline{w}_k .$$

The conditional probability densities of $\underline{a}_k$ given the states $S_1, S_2, \ldots, S_m$ are depicted for the 1-D (scalar) case

The Jacobian Matrix of the Measurement Vector is Derived for Use in the EKF

$$H \triangleq \left.\frac{\partial \underline{h}\left[\underline{x}_k\right]}{\partial \underline{x}_k}\right|_{\underline{x}_k = \hat{\underline{x}}_{k|k-1}}$$

$$= \begin{pmatrix} \dfrac{-10\eta\left(x_{k,1}-a_1\right)}{\ln(10)\left[\left(x_{k,1}-a_1\right)^2+\left(x_{k,4}-b_1\right)^2\right]} & 0 & 0 & \dfrac{-10\eta\left(x_{k,4}-b_1\right)}{\ln(10)\left[\left(x_{k,1}-a_1\right)^2+\left(x_{k,4}-b_1\right)^2\right]} & 0 & 0 \\ \dfrac{-10\eta\left(x_{k,1}-a_2\right)}{\ln(10)\left[\left(x_{k,1}-a_2\right)^2+\left(x_{k,4}-b_2\right)^2\right]} & 0 & 0 & \dfrac{-10\eta\left(x_{k,4}-b_2\right)}{\ln(10)\left[\left(x_{k,1}-a_2\right)^2+\left(x_{k,4}-b_2\right)^2\right]} & 0 & 0 \\ \dfrac{-10\eta\left(x_{k,1}-a_3\right)}{\ln(10)\left[\left(x_{k,1}-a_3\right)^2+\left(x_{k,4}-b_3\right)^2\right]} & 0 & 0 & \dfrac{-10\eta\left(x_{k,4}-b_3\right)}{\ln(10)\left[\left(x_{k,1}-a_3\right)^2+\left(x_{k,4}-b_3\right)^2\right]} & 0 & 0 \end{pmatrix}$$

The (3 x1) Measurement Vector is Highly Nonlinear

- Use RSSI signals from at least three (M_{BS}) base stations $(i = 1, \ldots, M_{BS})$
- *Known* base station location is $(a_{i,k}, b_{i,k})$ at discrete time $k = 0, 1, 2, \ldots$

$$\underline{z}_k = \underline{h}\left[\underline{x}_k\right] + \underline{v}_k = z_{0,i} - 10\eta \log_{10}\left(d_{k,i}\left[\underline{x}_k\right]\right) + v_{k,i}$$

- $\underline{z}_k$ denotes the RSSI measurement vector (3 x 1)
- RSSI signal modeled as sum of two terms:
  - Path loss $\underline{h}\left[\underline{x}_k\right] = z_{0,i} - 10\eta \log_{10}\left(d_{k,i}\left[\underline{x}_k\right]\right)$ where $d_{k,i}\left[\underline{x}_k\right] = \left[\left(x_k - a_{i,k}\right)^2 + \left(y_k - b_{i,k}\right)^2\right]^{1/2}$
  - Rician/Rayleigh Shadow fading $\underline{v}_{k,i} \sim N\left[0, \sigma_v^2\right]$
- Shadowing can considerably degrade estimation process, but prefiltering can be used to reduce observation noise [Zaidi et Al.]

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The Extended Kalman Filter for Mobility Estimation

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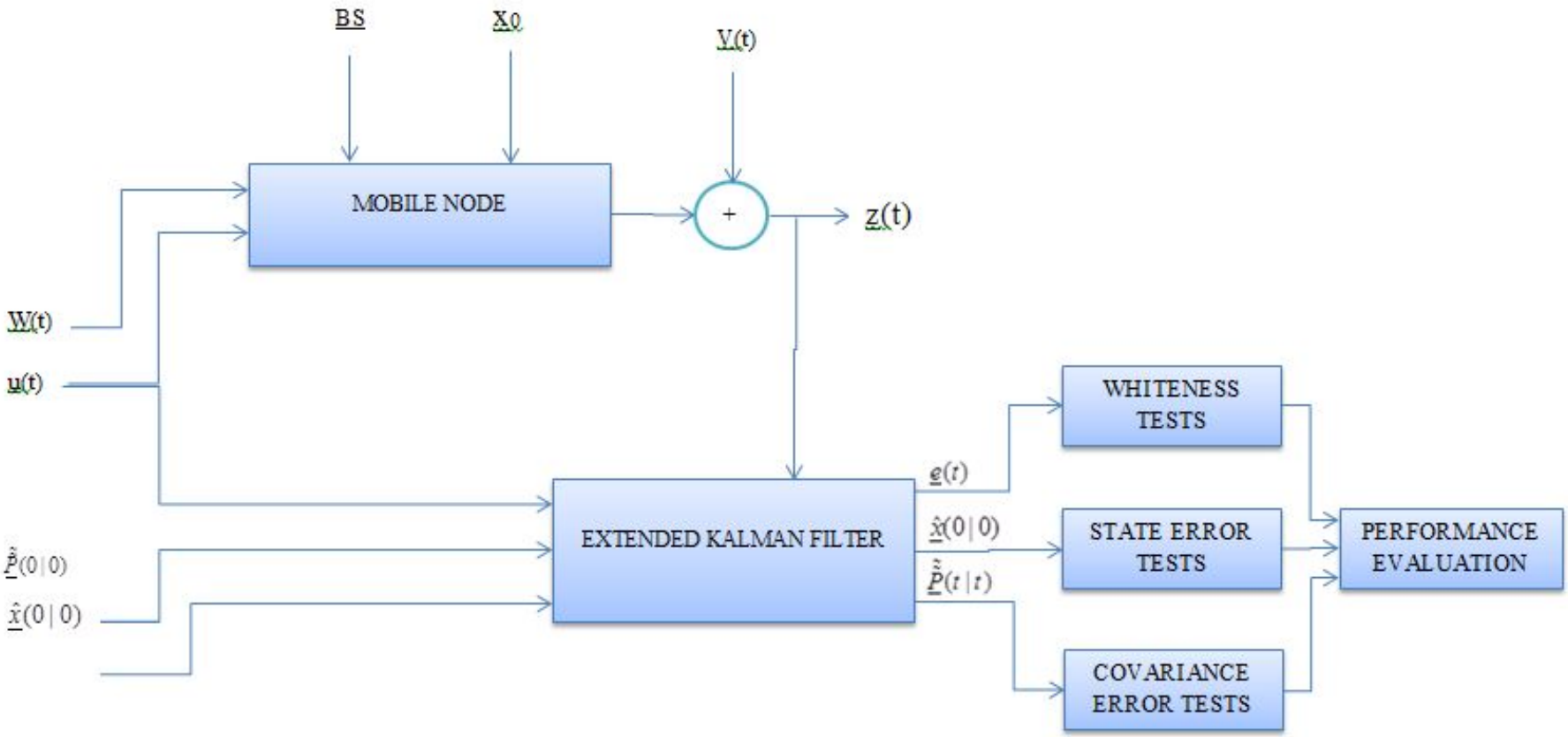
Our Dynamic Model is Linear and the Noises are Gaussian

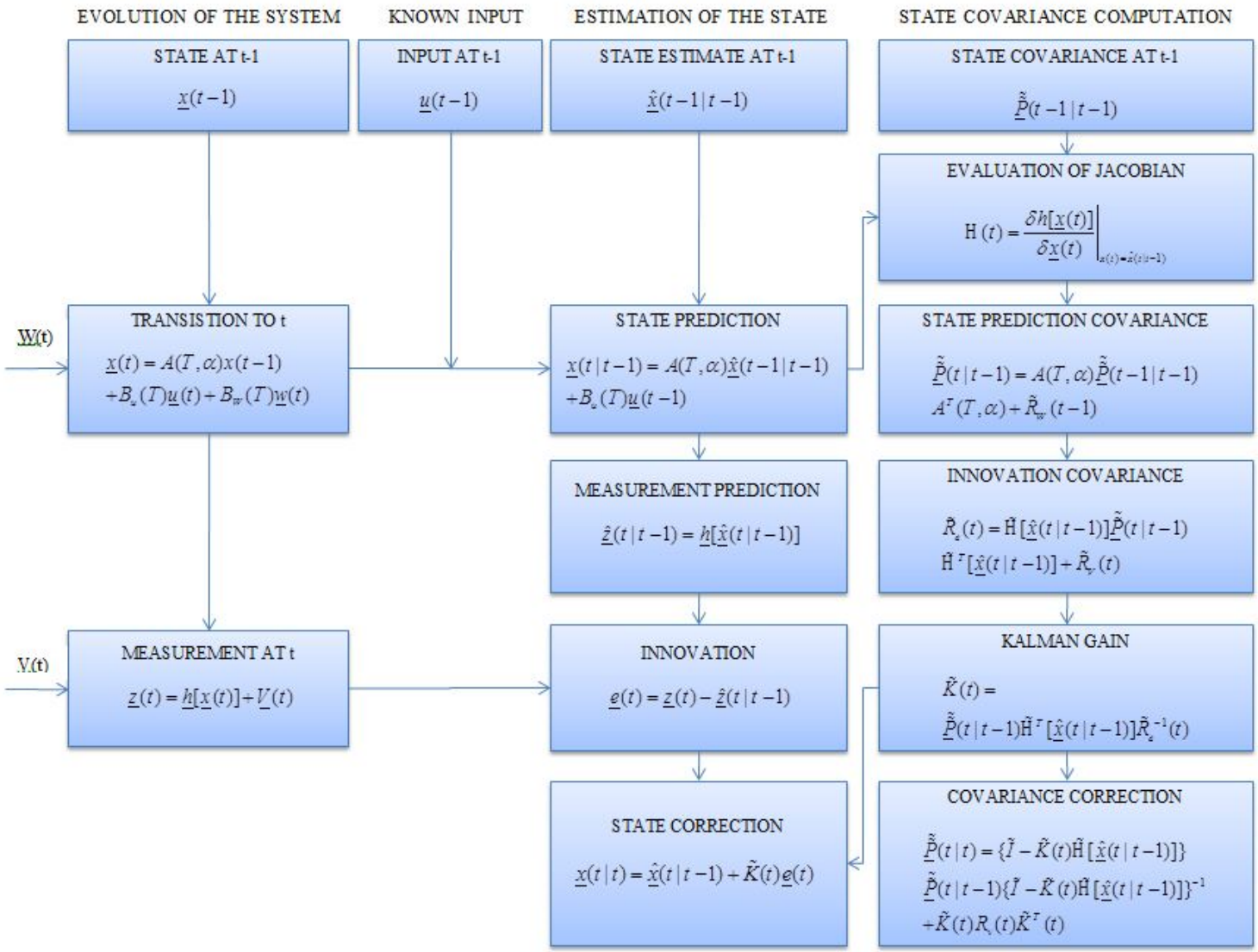
- Models based upon difference equations of the dynamics
  - In state space form or rational polynomial forms

- Model-Based Mobility Estimation algorithms
  - If Linear and Gaussian ➔ Kalman Filter
  - If Nonlinear and Gaussian ➔ Extended Kalman Filter or Unscented Kalman Filter
  - If Nonlinear and/or Non-Gaussian ➔ Sequential Monte Carlo estimator (Particle Filter)

The Extended Kalman Filter Uses the State-Space Model and RSSI Measurements



EKF Block Diagram



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Estimation Performance Measures

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We Define Performance Indices to Evaluate Estimation Performance and Tune the EKF

Zero-Mean Test on the Innovations

- Innovations must be zero mean and white for EKF to be optimal

$$\underline{e}(t) = \underline{z}(t) - \hat{\underline{z}}(t \mid t-1)$$

- the Expected Value of the innovations vector and its "two sigma bounds." If 95% of mean values lie within the bounds, the innovations are declared zero mean.

Innovations Whiteness Test

- The innovations "whiteness" indicates how well the EKF is tuned
- The autocorrelation function of a white stochastic process is a Kronecker delta function. We compute "two sigma bounds" on the autocorrelation and test the values at nonzero lags. If 95% of the samples lie beneath the bounds, then the Innovations are declared white

We Define Performance Indices to Evaluate Estimation Performance and Tune the EKF

Root Mean Squared State Estimation Error

- The state estimation error is given by:

$$\underline{\tilde{x}}_k \triangleq \underline{x}_k - \underline{\hat{x}}_{k|k-1} \qquad E\left[\underline{\tilde{x}}_k^T \underline{\tilde{x}}_k\right] = MSE\left(\underline{\tilde{x}}_k\right)$$

$$\sigma_{\underline{\hat{x}}} \triangleq \sqrt{\mathrm{var}\left(\underline{\tilde{x}}_k\right)}$$

- We calculate the state estimation error vector and its "two sigma bounds." If 95% of values lie within the bounds, the innovations are declared zero mean.

We Define Performance Indices to Evaluate Estimation Performance and Tune the EKF

Weighted Sum Squared Residual *(WSSR)*

- Multiple innovations whiteness testing (aggregates innovations into a scalar performance measure)

  If 95% of the WSSR values lie beneath the threshold, then we declare the EKF tuned.

WSSR for $(p \times 1)$ Vector Innovations

$$\gamma(l) = \sum_{k=l-W+1}^{l} \underline{e}^T(k) R_e^{-1}(k) \underline{e}(k) \quad , \quad \text{for } l > W$$

$$R(i,k) = \frac{1}{W} \sum_{t=k+1}^{W} \left[e_i(t) - m_e(i) \right] \left[e_i(t+k) - m_e(i) \right]$$

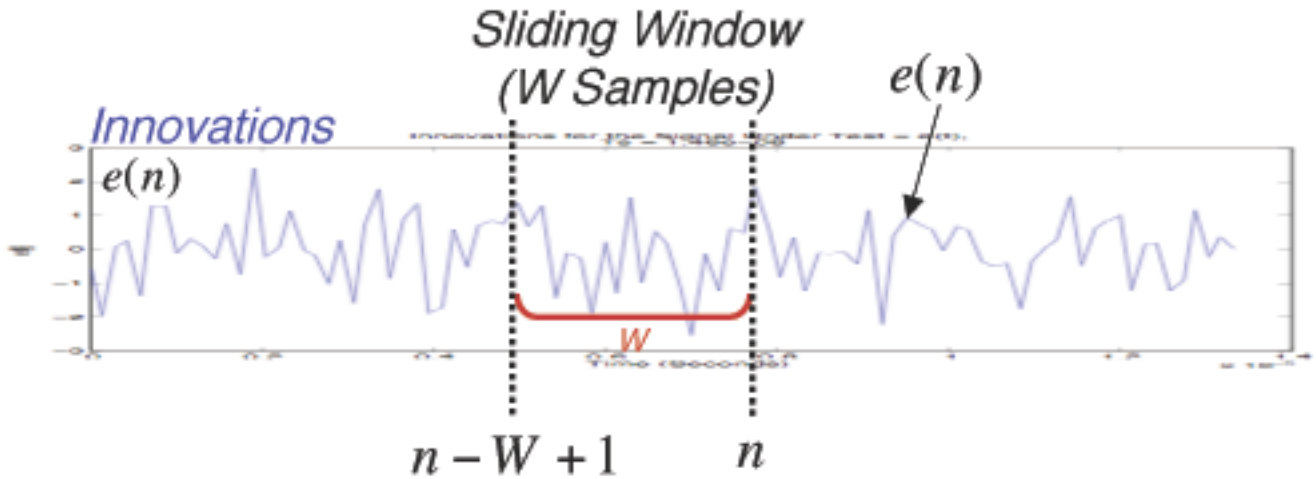
$$m_e(i) = \frac{1}{W} \sum_{t=1}^{W} e_i(t) \quad , \quad \text{for } i = 1, 2, \ldots, p$$

Hypothesis Test

$$\gamma(l) \underset{H_0}{\overset{H_1}{\gtrless}} \tau$$

τ = Decision Threshold

Example: How to Compute the Scalar WSSR for a Scalar Innovations Sequence



$$\gamma(n) = \sum_{j=n-W+1}^{n} \frac{e^2(j)}{V(j)}, \quad \text{for } n \geq W$$

$$V(n) = \frac{1}{W} \sum_{j=n-W+1}^{n} \left[e(j) - \bar{e}(j)\right]^2, \quad \text{for } n \geq W$$

$$\bar{e}(n) = \frac{1}{W} \sum_{j=n-W+1}^{n} e(j), \quad \text{for } n \geq W$$

The PCRLB Gives a Lower Bound on the Achievable State Estimation Error Variance

Posterior Cramer-Rao Lower Bound *(PCRLB)*

- Lower bound on achievable variance in the estimation of a parameter gives a reference point from which to evaluate estimator uncertainty
- The covariance matrix of the state estimate error is:

$$P_{k|k} = E_{k,\underline{x}}\left[\left(\hat{\underline{x}}_{k|k} - \underline{x}_k\right)\left(\hat{\underline{x}}_{k|k} - \underline{x}_k\right)^T\right] \geq J_k^{-1}$$

- The Fisher Information Matrix using likelihoods lambda

$$J_k = E_{\underline{x}_k}\left\{\left[\nabla_{\underline{x}_k}\lambda\left(\underline{x}_k\right)\right]\left[\nabla_{\underline{x}_k}\lambda\left(\underline{x}_k\right)\right]'\right\}\Bigg|_{\underline{x}_k=\underline{x}_0}, \qquad \lambda\left(\underline{x}_k\right) = \ln p\left(\underline{x}^* \mid \underline{x}_k\right)$$

- The PCRLB for this problem is

$$PCRLB = \sqrt{P_{k|k}\left(1,1\right) + P_{k|k}(4,4)}.$$

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Simulation Experiment and Performance Measurement

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Initial State and State Covariance Estimates

Parameter	Values
Initial state covariance estimate	$\begin{pmatrix} 400^2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 15^2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 5^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 400^2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 15^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 5^2 \end{pmatrix}$
Initial state estimate	$\begin{pmatrix} 3400 \\ 5 \\ 0 \\ 8700 \\ 8 \\ 0 \end{pmatrix}$

Simulation Experiment Setup

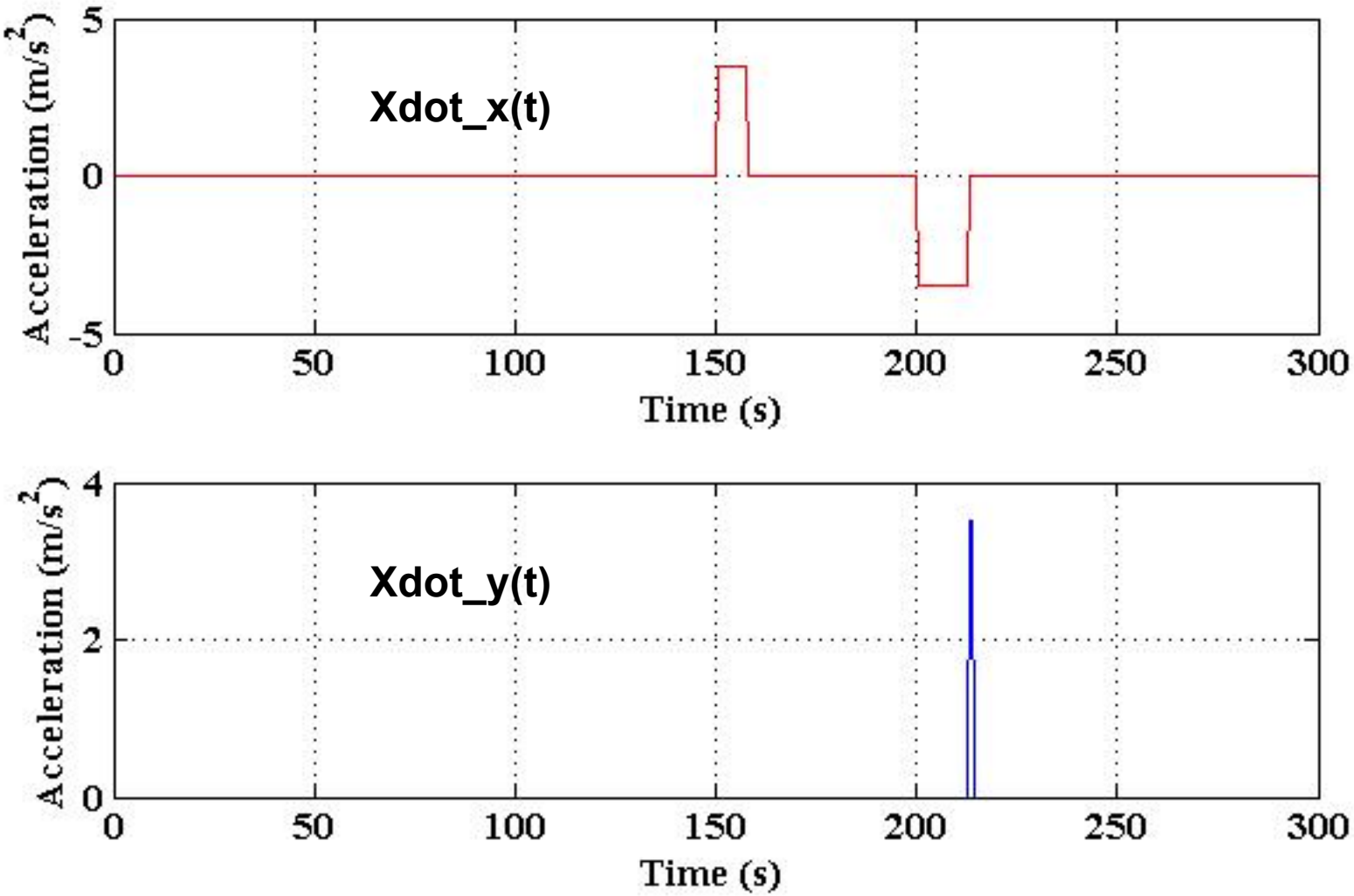
Simulate the Command Input

- Generated manually; assumed to have zero process noise (deterministic)
- Short-time maneuvers are followed by uniform motion
- Discrete acceleration levels $M = \{(0.0, 0.0), (3.5, 0.0), (0.0, 3.5), (0.0, -3.5), (-3.5, 0.0)\}$

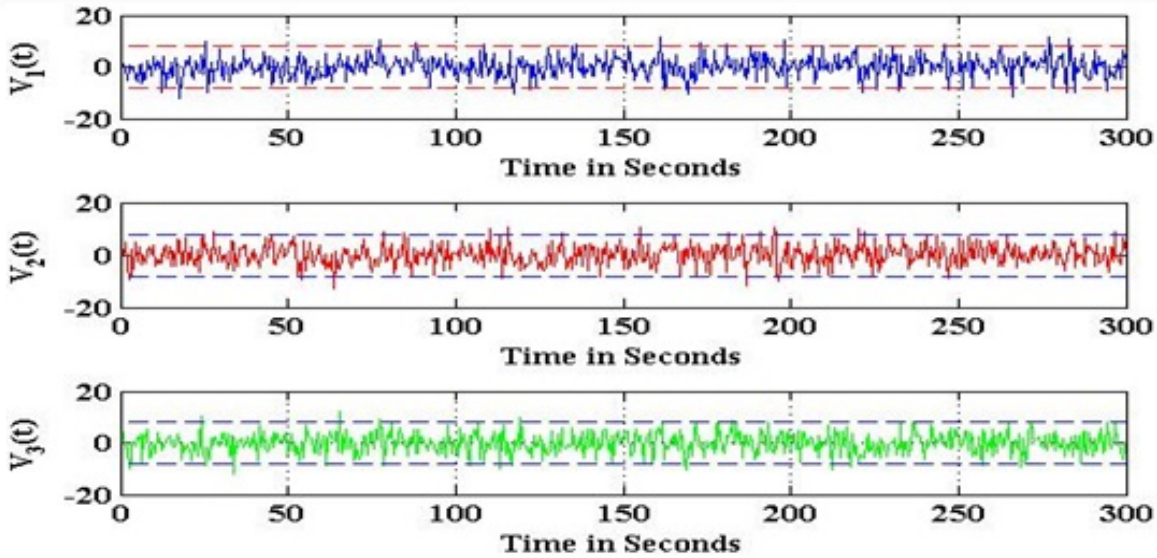
Simulate the Uncertainties

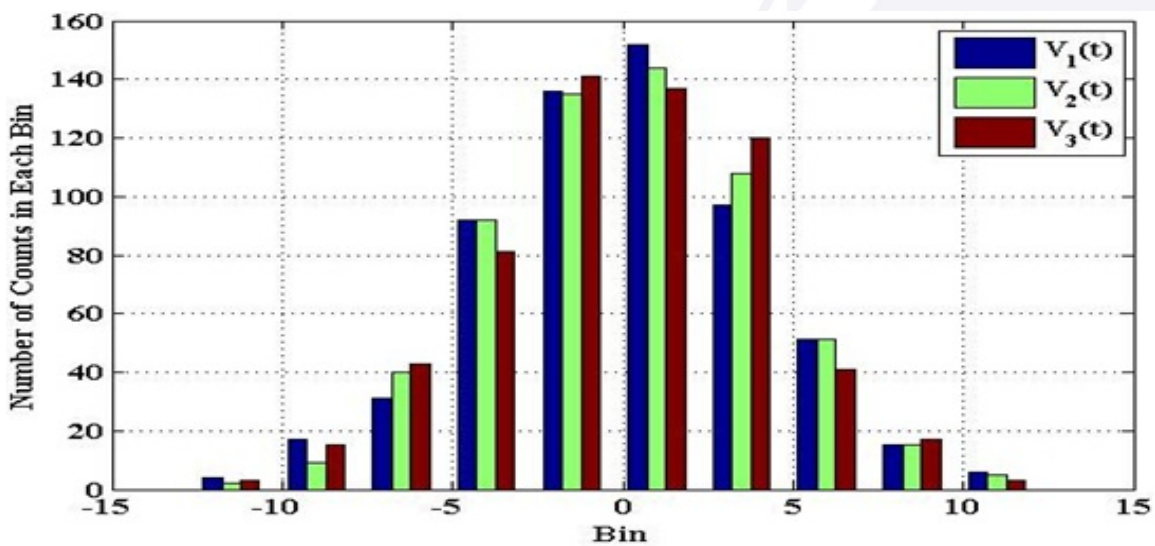
- White noise sequences mimic the changing UGV-DTN node (zero mean, white Gaussian process noise and the noisy signal measurement (zero mean, white Gaussian

The (2 x 1) Acceleration Vector is Designed to Create a Trajectory Having two Turns, the 2nd one Very Sharp



Measurement Noise Vector v(k (For 3 Base Stations)

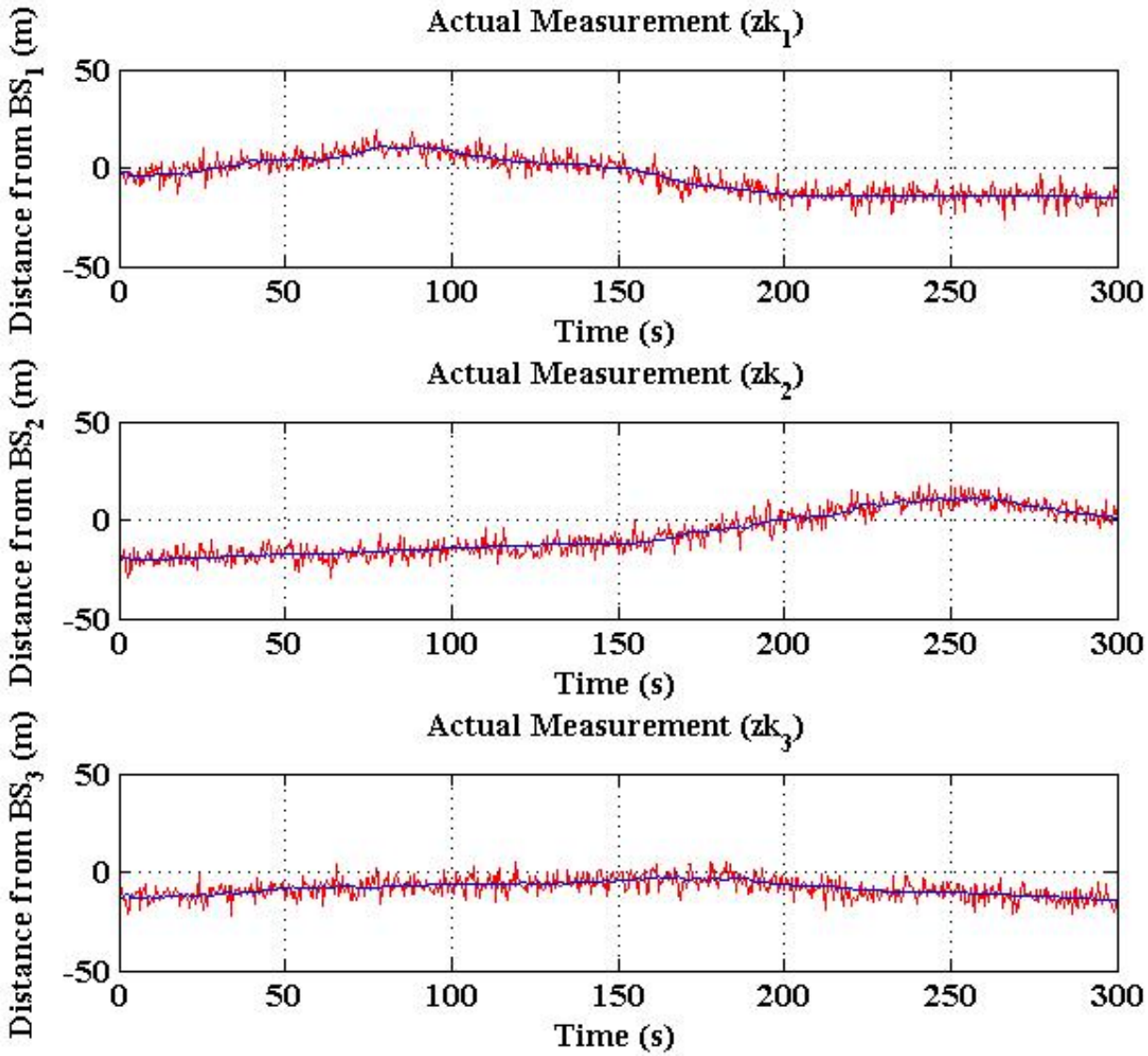




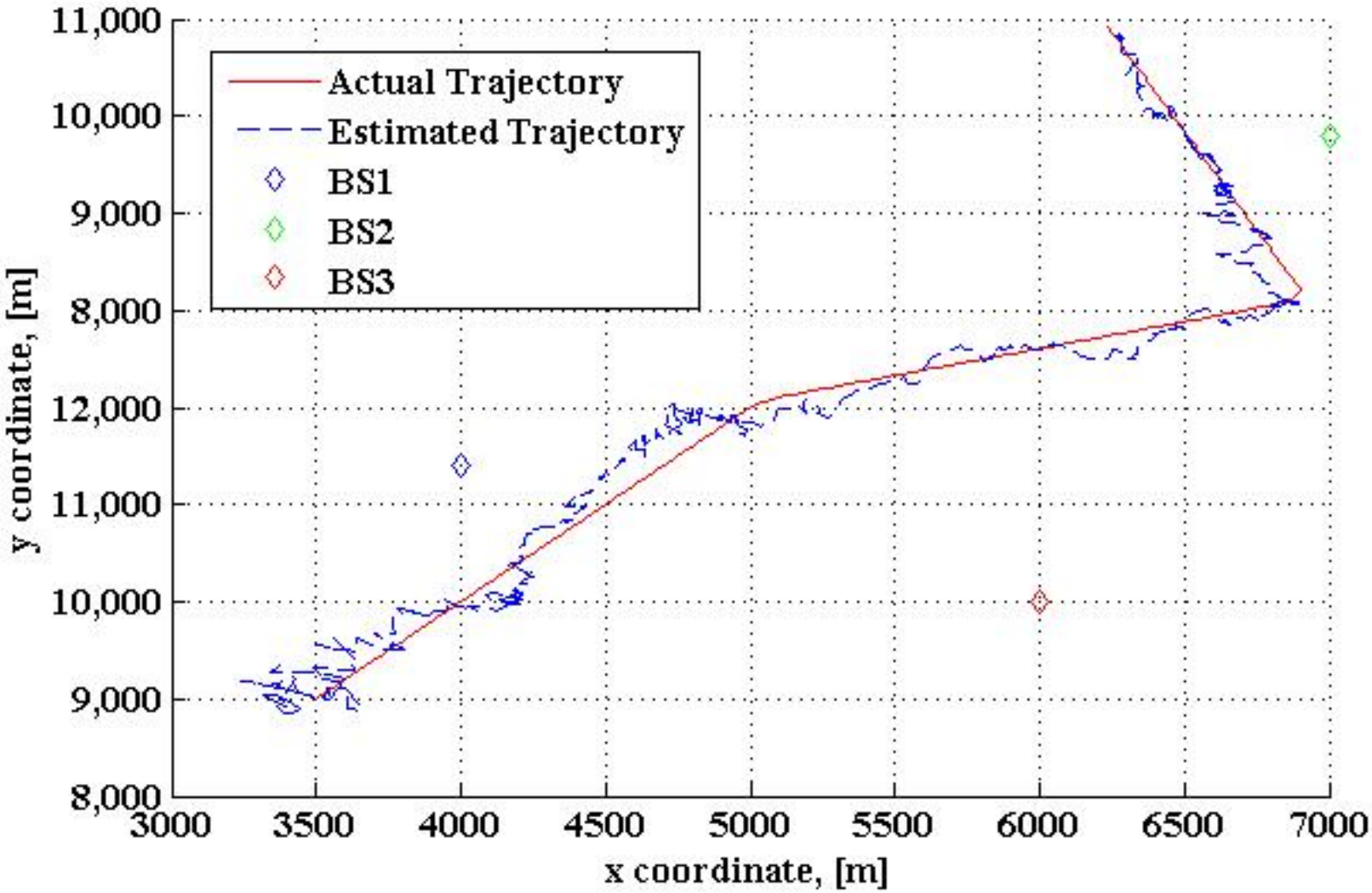
$$\underline{v}_k \rightarrow N[0,8I]$$

$$\pm 2\sigma_v = \pm 8$$

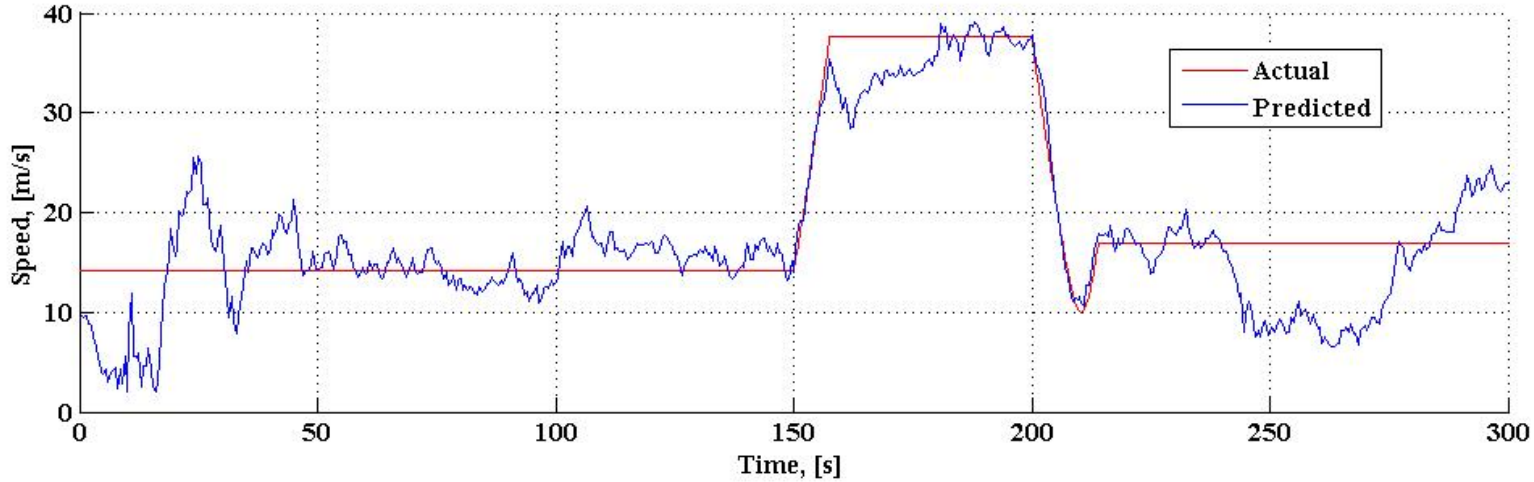
Noisy RSSI Measurement Signals: Distances from the 3 Base Stations

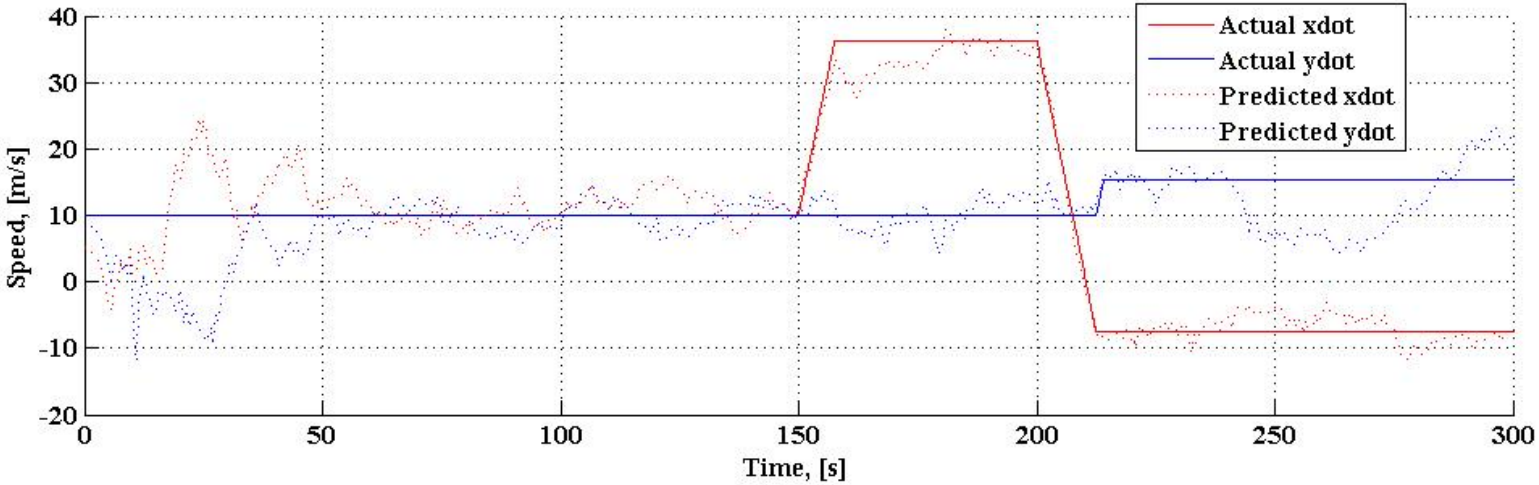


The Estimated Trajectory Tracks the Actual Trajectory Nicely, Even Through a Tight Turn

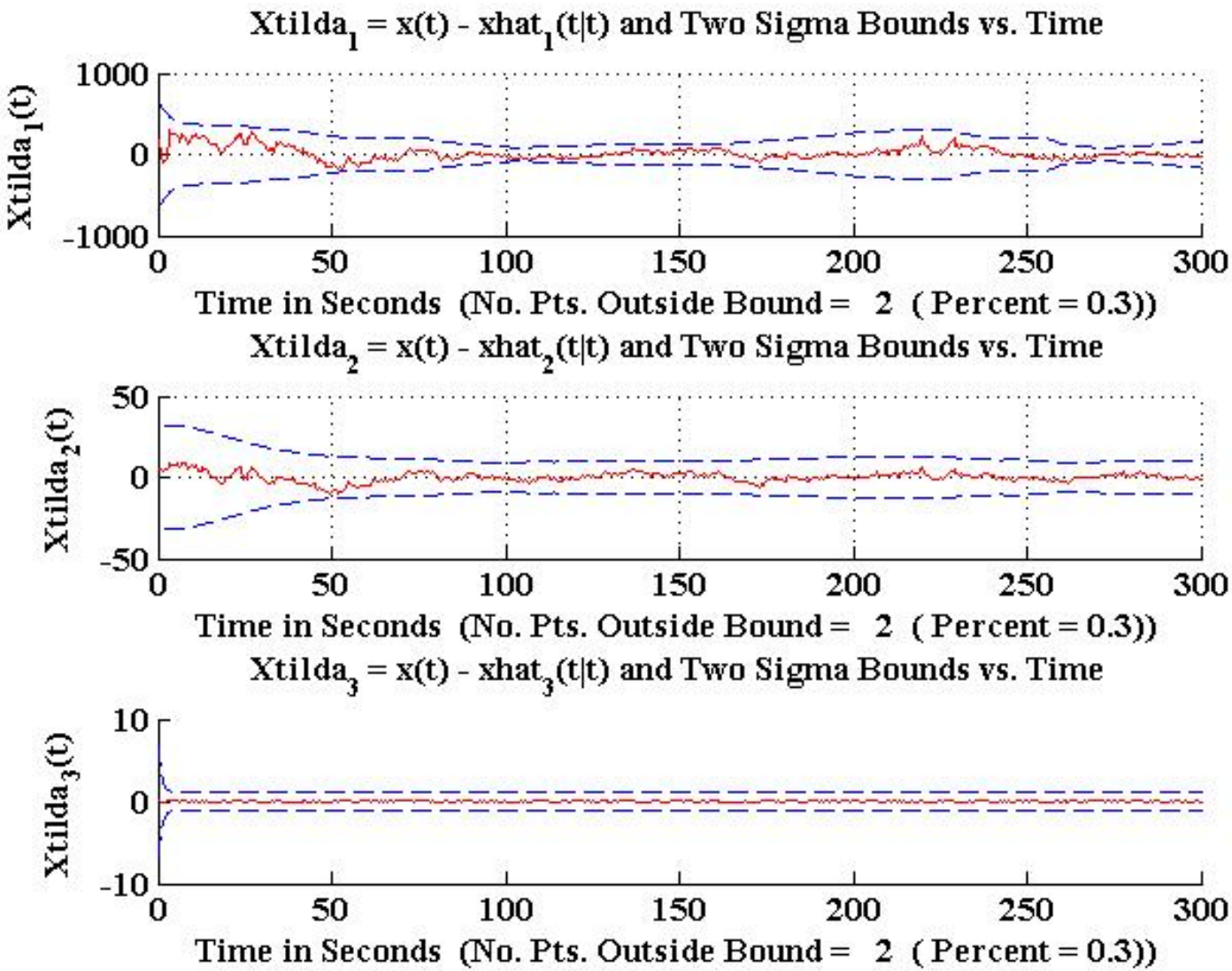


Top: Actual and Estimated RMS Speed (x and y combined)
Bottom: Actual and Predicted Speeds xdot and ydot

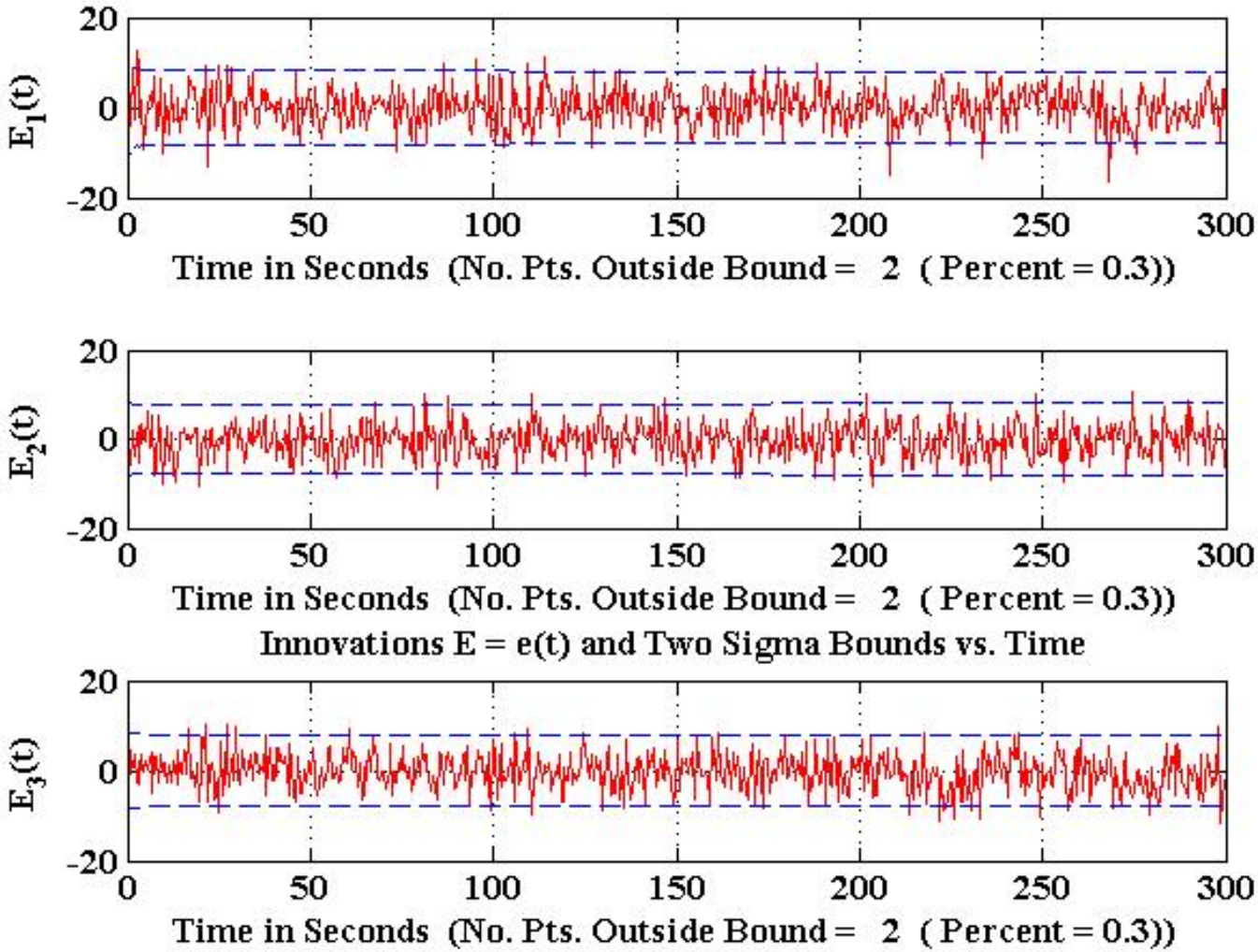




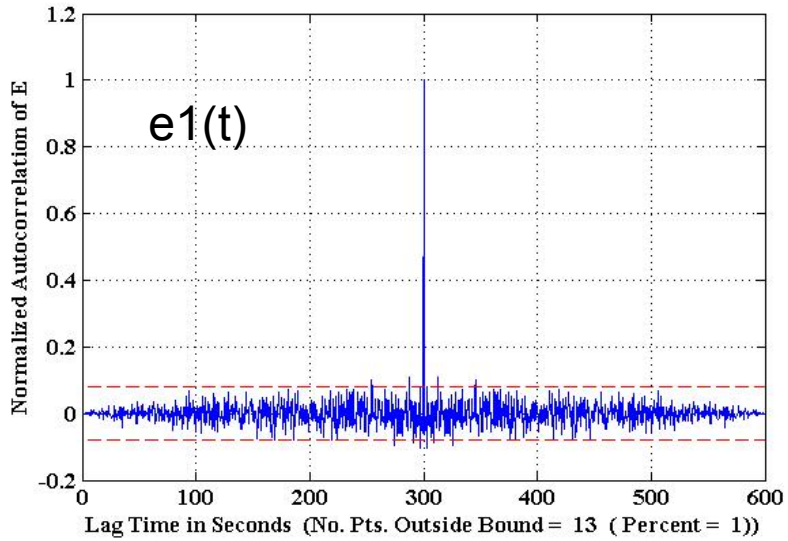
State Error Vector Xtilda(k) = x(k) – xhat(k|k) and its "Two Sigma Error Bounds" vs. Time

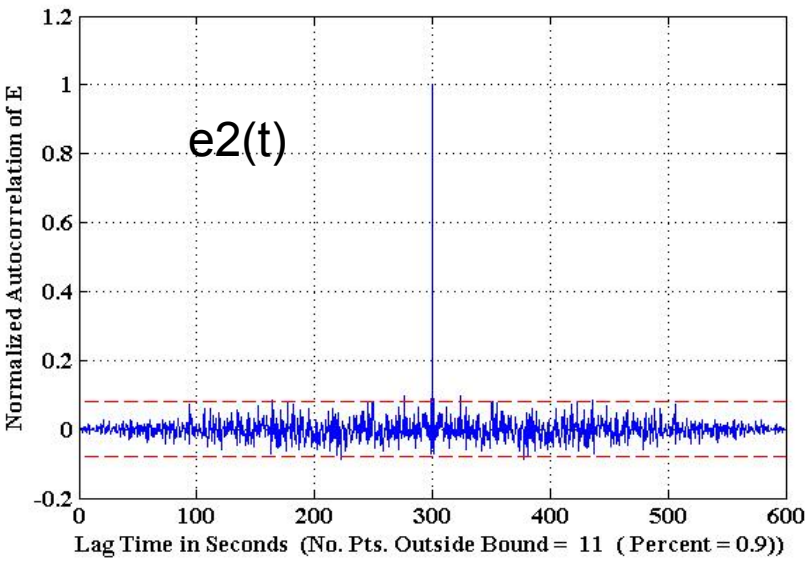


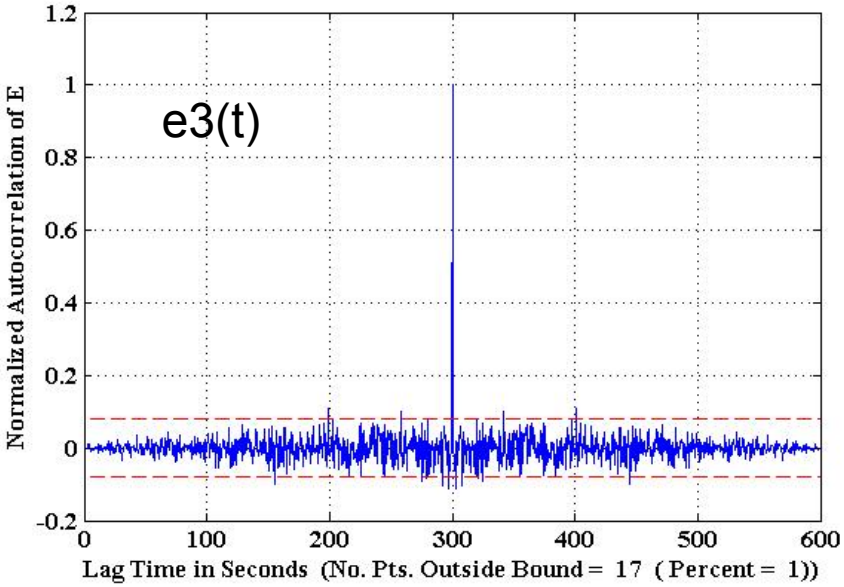
Innovations Vector e(t) and "2 Sigma Error Bounds"
e(k) = z(k) – zhat(k|k-1)



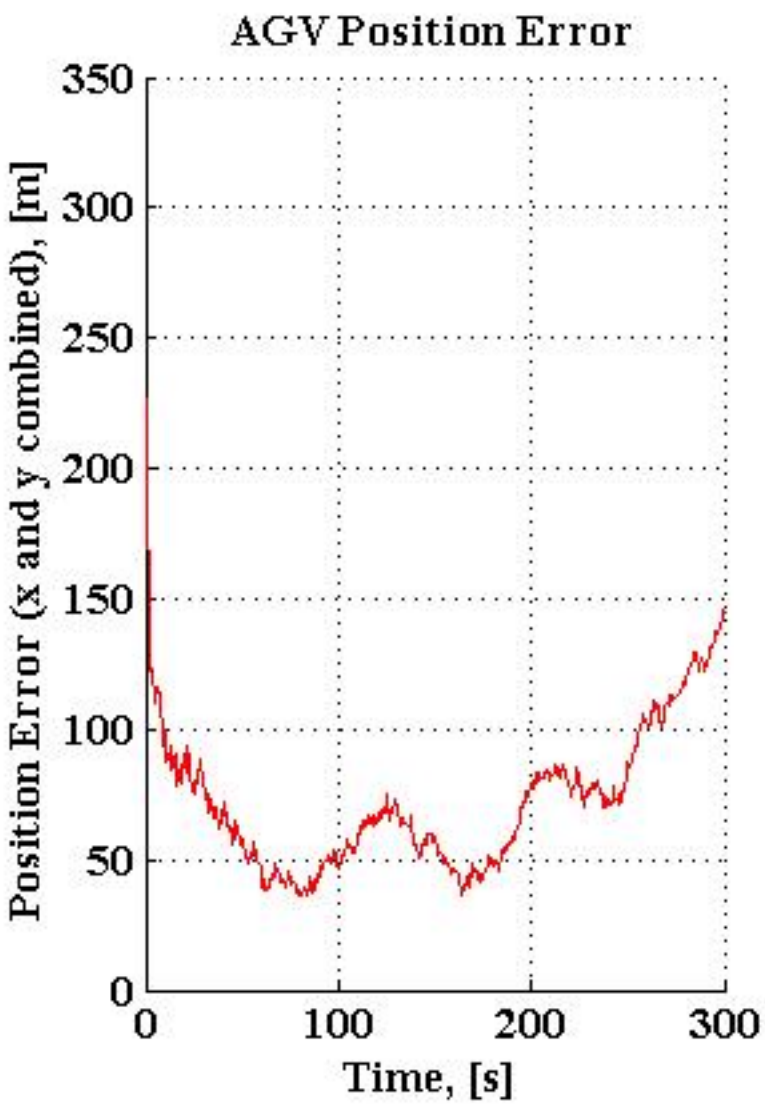
Statistical Whiteness Test on the Innovations e(k) = z(k) – zhat(k|k-1)



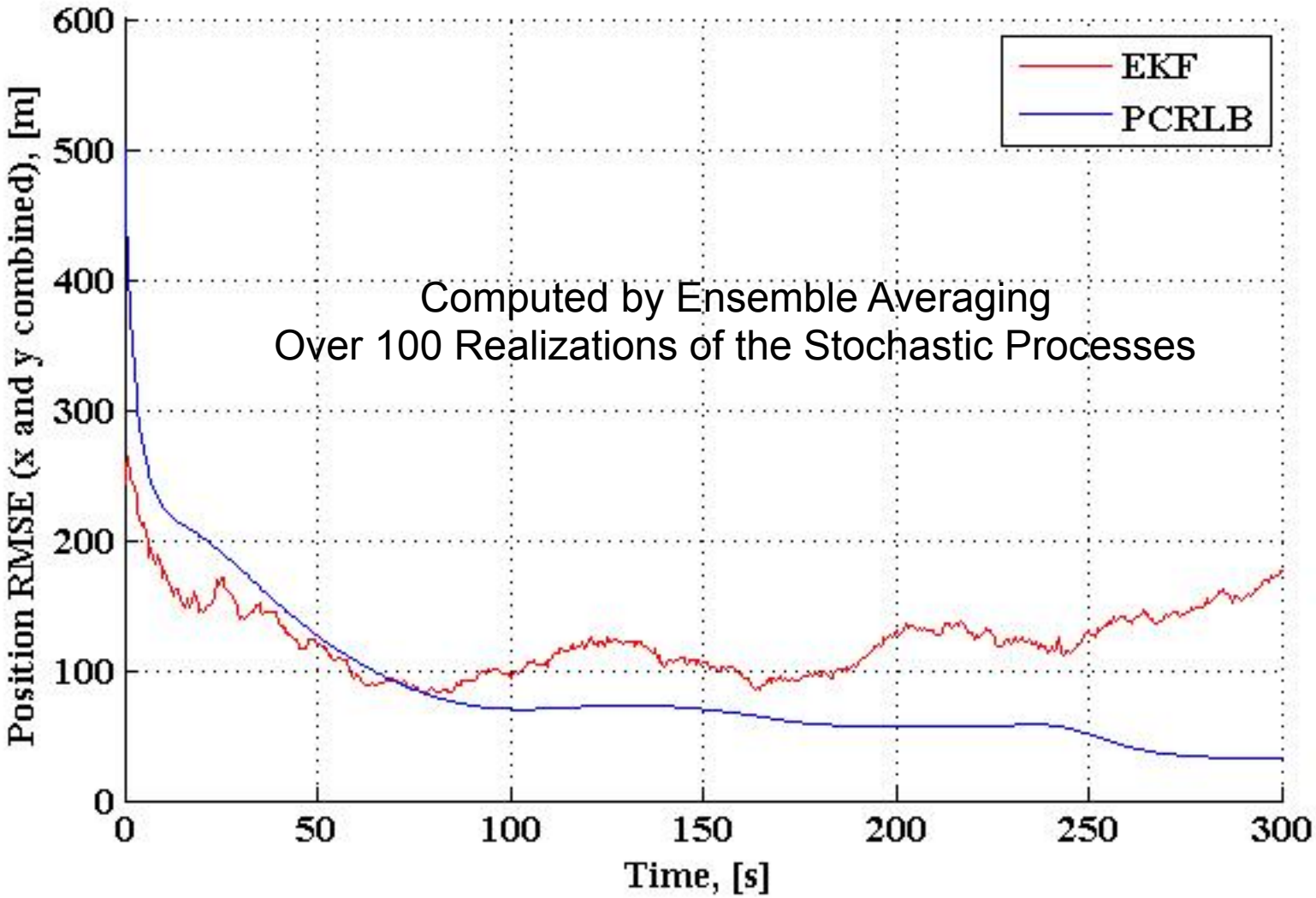




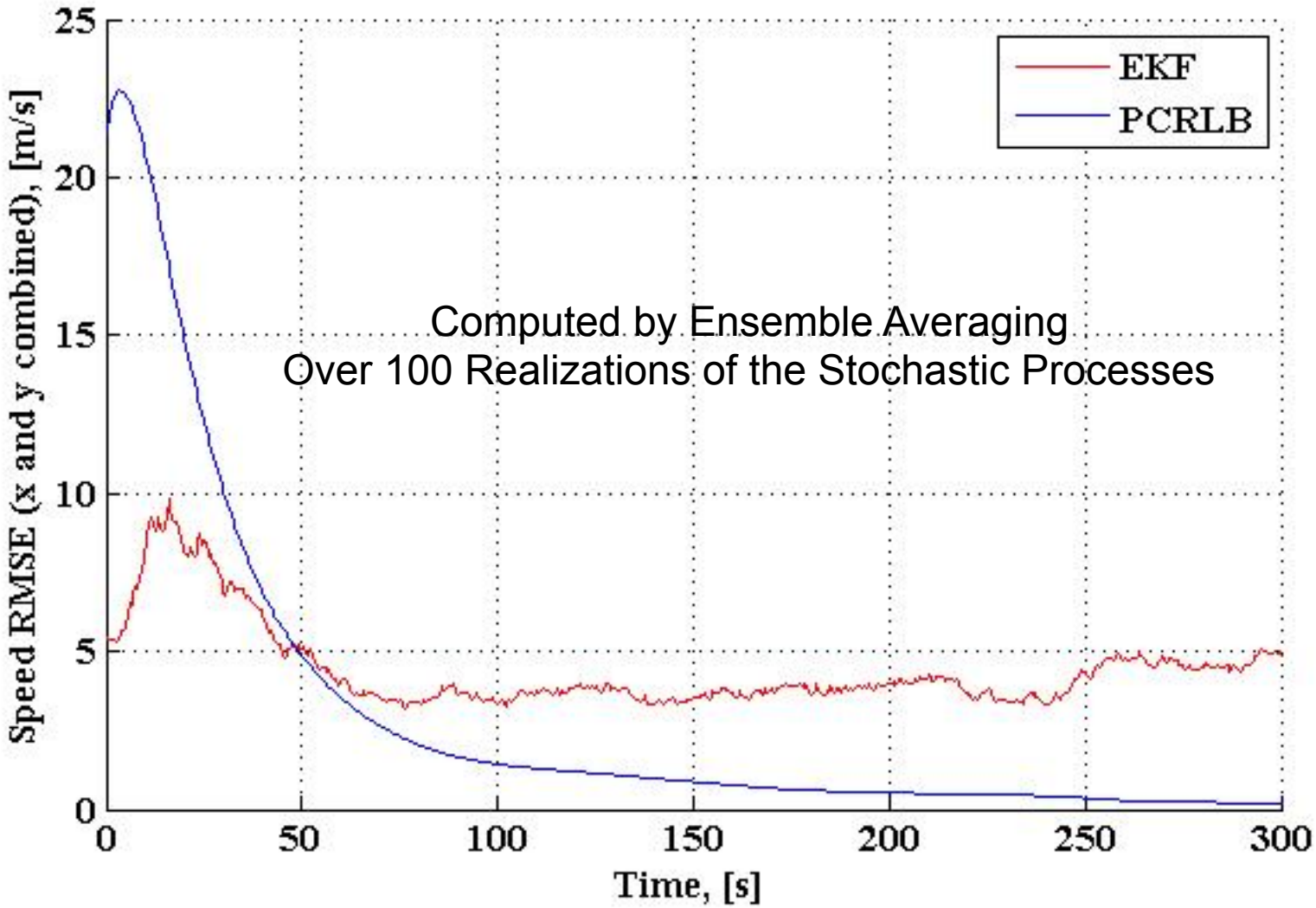
Position Error and Speed Error vs. Time (x and y Components are Combined)



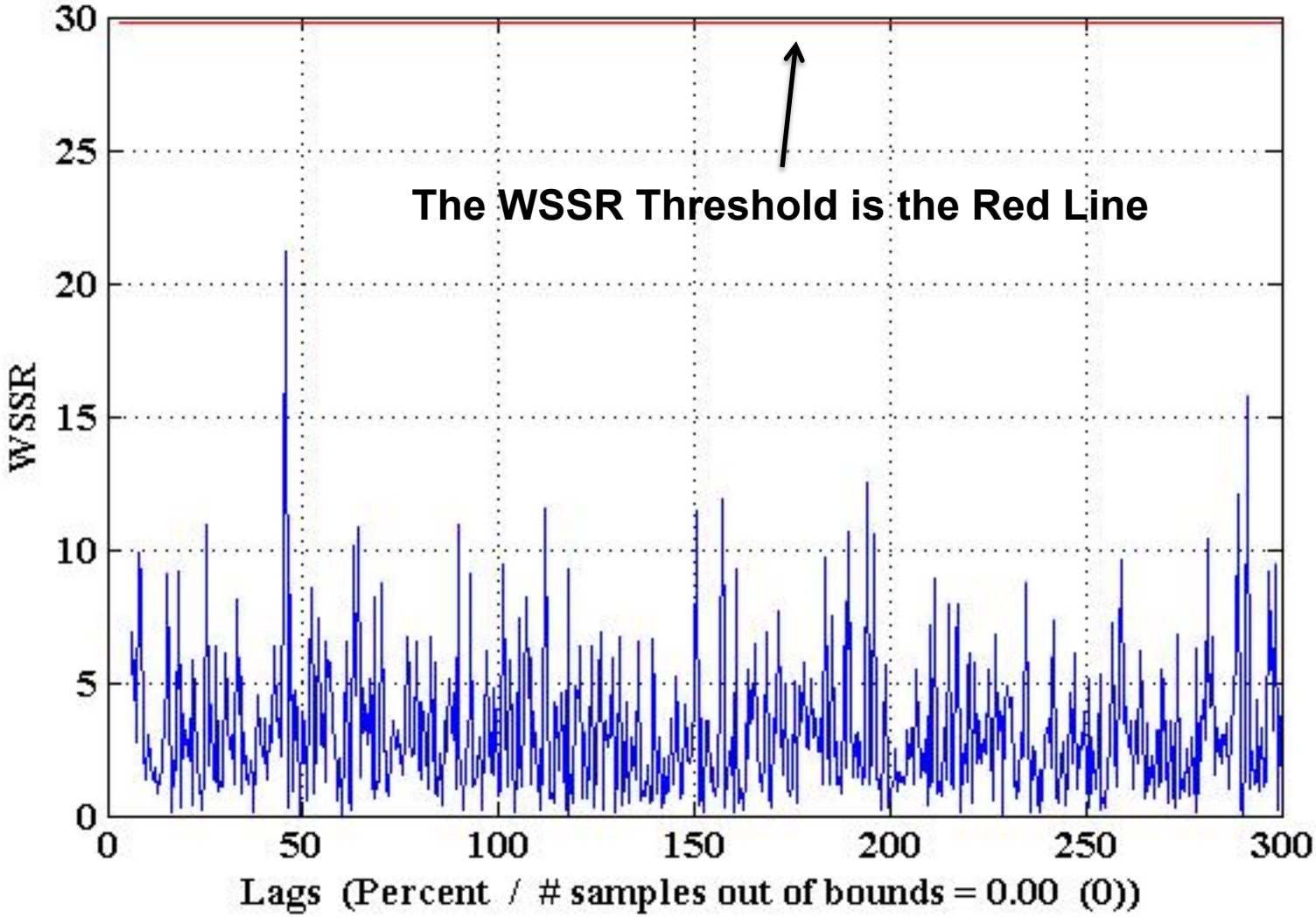
Red: Position RMS (x and y combined)
Blue: PCRLB on the Position RMS



Red: Speed RMS (x and y combined)
Blue: PCRLB on the Speed RMS



WSSR (Weighted Sum Squared Residuals) Are Well Below the Threshold (Red), So the EKF is Well Tuned



Conclusions and Future Work

Conclusions

- The algorithm is shown to implement efficient mobility tracking of UGV nodes in a wireless network
- Demonstrated that the mobility estimator performs effectively and can be integrated into a new cooperative routing protocol with enhanced performance

Future Work

- Combination with a new routing algorithm
- Utilization of GPS-Enabled anchor nodes
- Estimation using a Rao-Blackwellized particle filter
- Estimation using actual UGV-DTN node mobility data

NAVAL
POSTGRADUATE
SCHOOL

Contingency VG's

Simulation Experiment Results

- EKF highly sensitive to choice of initial conditions on the state vector and state vector covariance
  - Prior knowledge allows better choices for initial conditions
  - Closer the initial state vector and covariance matrix are to the true state vector and state covariance matrix, the more rapidly the EKF will converge to proper solution
- EKF initial conditions determine the reaction of the UGV-DTN node in order to converge to the desired state
  - The more confidence you have in your initial conditions, implying low uncertainty or initial covariance levels, the slower the UGV-DTN initially reacts to changes in the desired states
  - The node behavior normalizes over time, implying that the filter eventually converges to the desired solution in finite time
  - ICs will likely prove a useful parameter to tailor the initial behavior to suit proposed UGV-DTN routing algorithms

Simulation Experiment

We Simulate to Demonstrate and Validate the Algorithm

- Simulate single node traveling along a trajectory that includes abrupt maneuver with process noise assumed to be zero (deterministic track)
- Gauss-Markov state space model with semi-Markov chain for node dynamics
- Constant power RSSI signal transmitted from three fixed position base stations

Simulation and EKF Initial Parameters

1) Simulation parameters follow from Ristic et al. for basis of evaluation
2) Initial state and state covariance estimates for the EKF

Measurements from One UGV (One Node) in a Cluster

One UGV Node

Acceleration Vector $= \underline{a}(t)$

Velocity Vector $= \underline{v}(t)$

Position Vector $= \underline{p}(t)$

RSSI Information $= \underline{r}(t)$

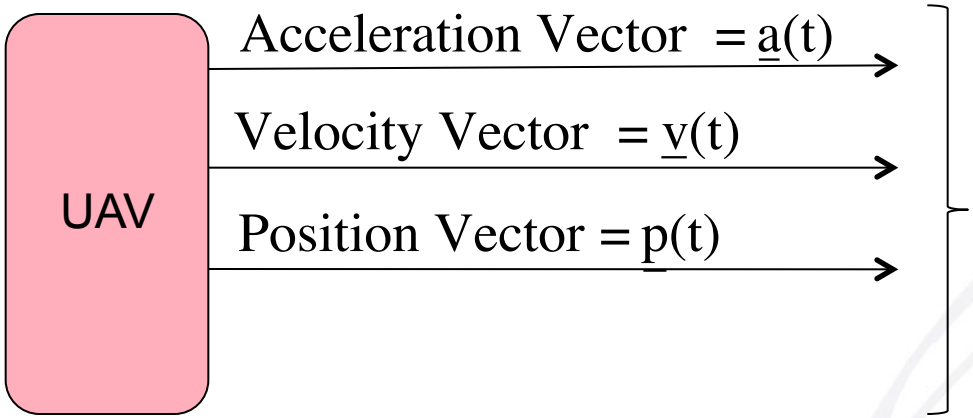
$$\underline{X}_{Node} = \begin{bmatrix} \underline{a}(t) \\ \underline{v}(t) \\ \underline{p}(t) \\ \underline{r}(t) \end{bmatrix}$$

RSSI = Received Signal Strength Indicator

$\Rightarrow$ Power of the Signal Received at the Antenna

$$\underline{X}_C = \text{Measurement Vector from Cluster} = \begin{bmatrix} \underline{X}_{CR} \\ \underline{X}_{CM} \end{bmatrix} = \begin{bmatrix} \text{Measurements Needed for Routing} \\ \text{Measurements Needed for Mobility} \end{bmatrix}$$

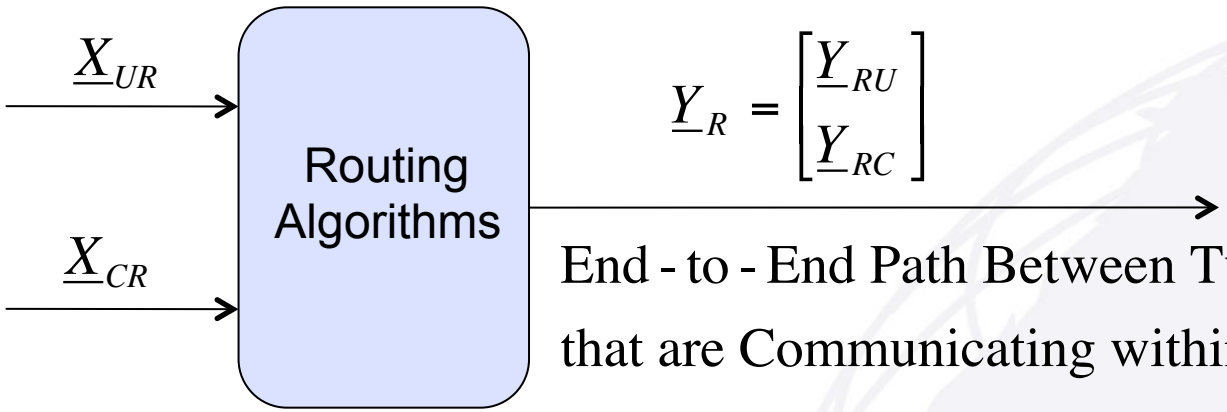
Measurements from the UAV



$$\underline{X}_U = \begin{bmatrix} \underline{a}(t) \\ \underline{v}(t) \\ \underline{p}(t) \end{bmatrix}$$

$$\underline{X}_U = \text{Measurement Vector from UAV} = \begin{bmatrix} \underline{X}_{UR} \\ \underline{X}_{UM} \end{bmatrix} = \begin{bmatrix} \text{Measurements Needed for Routing} \\ \text{Measurements Needed for Mobility} \end{bmatrix}$$

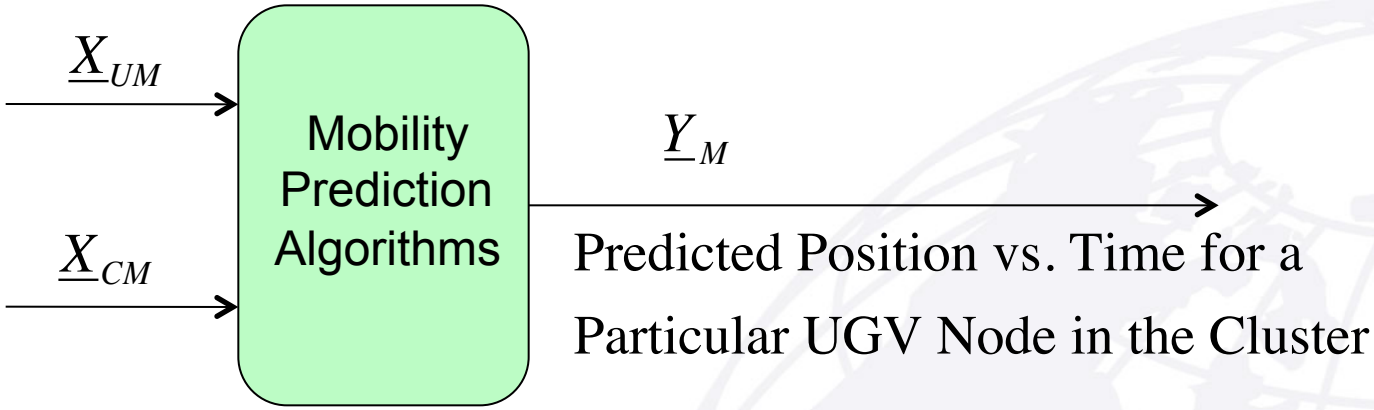
Outputs from the Routing Algorithms



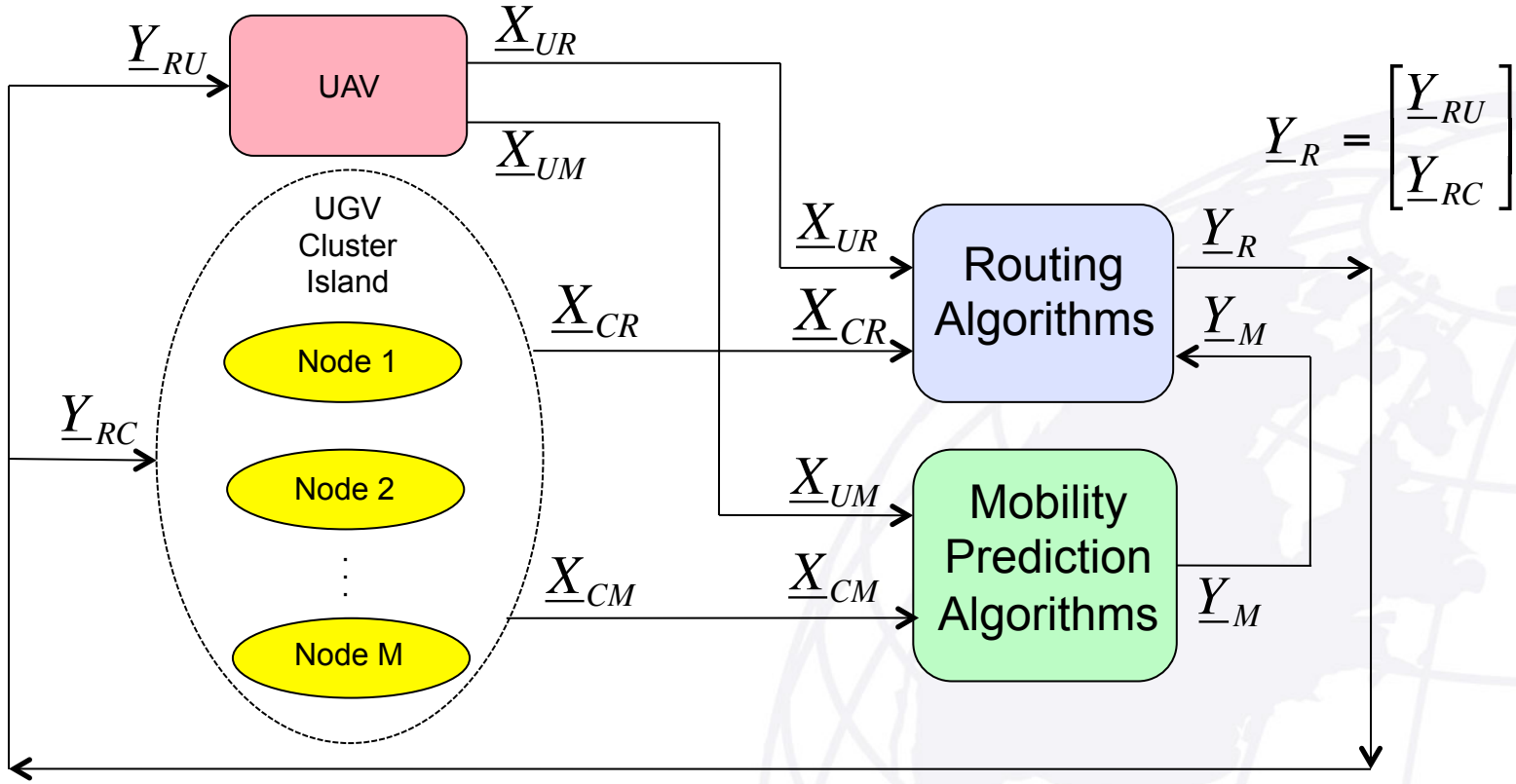
$$\underline{Y}_R = \begin{bmatrix} \underline{Y}_{RU} \\ \underline{Y}_{RC} \end{bmatrix}$$

End - to - End Path Between Two Nodes that are Communicating within the Cluster

Our Focus is on the Mobility Prediction Algorithms



UAV and UGV Information Flow



$$\underline{X}_U = \text{Measurement Vector from UAV} = \begin{bmatrix} \underline{X}_{UR} \\ \underline{X}_{UM} \end{bmatrix} = \begin{bmatrix} \text{Measurements Needed for Routing} \\ \text{Measurements Needed for Mobility} \end{bmatrix}$$

$$\underline{X}_C = \text{Measurement Vector from Cluster} = \begin{bmatrix} \underline{X}_{CR} \\ \underline{X}_{CM} \end{bmatrix} = \begin{bmatrix} \text{Measurements Needed for Routing} \\ \text{Measurements Needed for Mobility} \end{bmatrix}$$

Operational Needs Drive Our Work

- ***Integrate communications networking and information sharing into tactical military operations***

- ***Mobile Ad Hoc Networks (MANET)***
  - Require rapidly deployable networks, adapting to new environments
  - Mobile infrastructures, relying on wireless and self-organizing units

Issues in Survivable MANET's

- ***Routing: Maintaining, Improving Communication Connectivity***
  - Node/link failure mitigation -> survivability
  - Distributed Mobile Communications
- ***Resource Management and Distribution***
  - Capacity and bandwidth allocation
- ***Quality of Service provisioning***
  - Maintain reliability of services in different network conditions

Our Focus: Resource Allocation & Routing

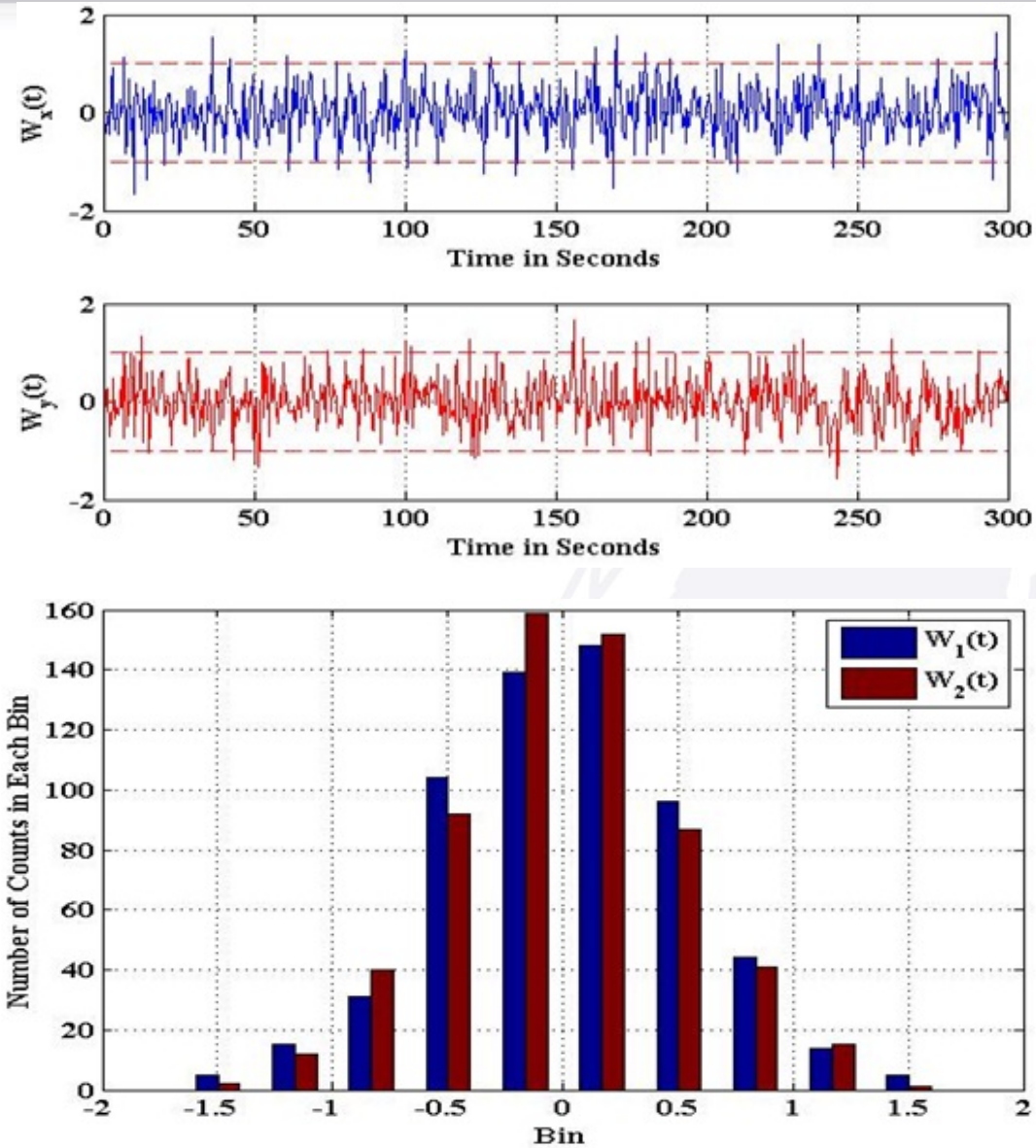
- ***We Need To Control And Route Resources:***
  - Bandwidth
  - Channel Capacity
  - Channel Assignments
  - Scheduling: e.g. When users can transmit
  - Power allocation for each user
  - Etc.

- ***This Requires Mobility Prediction:***

  → *Estimating and predicting:*

  - User locations over time (trajectories)
  - Likely wireless access points (AP's) to which user will connect
  - Resource usage over time

Process Noise Vector w(t)



The General Single Input Single (SISO) System Model

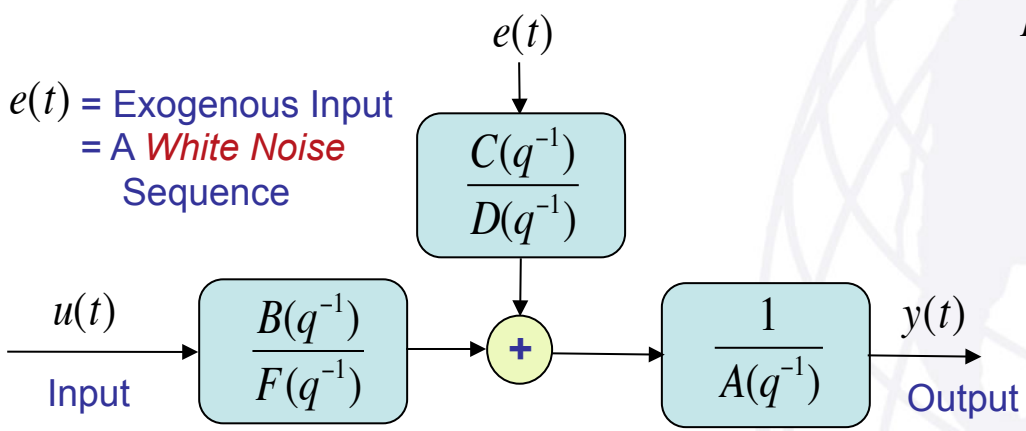
Lennart Ljung, Linkoping, Sweden

General SISO System Model :

$$A(q^{-1})y(t) = \frac{B(q^{-1})}{F(q^{-1})}u(t) + \frac{C(q^{-1})}{D(q^{-1})}e(t)$$

or : $$y(t) = \frac{B(q^{-1})}{A(q^{-1})F(q^{-1})}u(t) + \frac{C(q^{-1})}{A(q^{-1})D(q^{-1})}e(t)$$

$e(t)$ = Exogenous Input
= A *White Noise* Sequence



Where :

q^{-1} = Delay Operator

$$A(q) = 1 + a_1 q^{-1} + a_2 q^{-2} \cdots + a_{N_a} q^{-N_a}$$

$$B(q) = b_0 + b_1 q^{-1} + b_2 q^{-2} \cdots + b_{N_b} q^{-N_b}$$

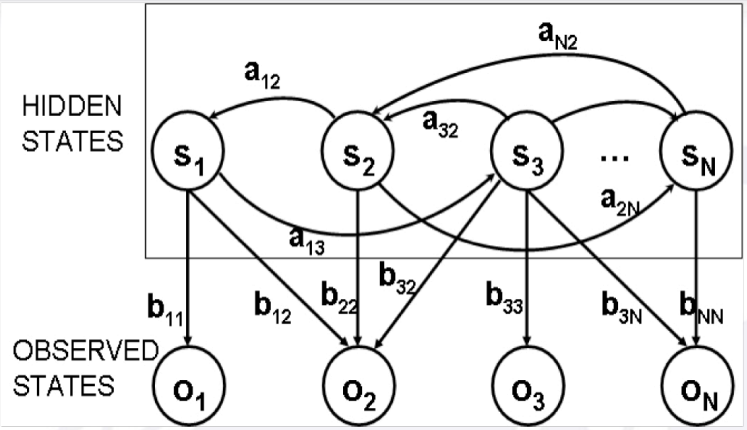
$$C(q) = 1 + c_1 q^{-1} + b_2 q^{-2} \cdots + b_{N_c} q^{-N_c}$$

$$D(q) = 1 + d_1 q^{-1} + d_2 q^{-2} \cdots + d_{N_d} q^{-N_d}$$

$$F(q) = 1 + f_1 q^{-1} + f_2 q^{-2} \cdots + f_{N_f} q^{-N_f}$$

My Focus: Mobility Modeling and Prediction

- We need Signal Processing and Control
- Models are probabilistic and dynamic: Mo(e.g. Hidden Markov Models)



- *Three Key Problems We Need to Solve:*

(1) Given: Observed movement sequence "O" over time,
Estimate: Probability that "O" was generated by model λ

(2) Given: Observed movement sequence "O" over time,
Estimate: Locate the hidden parameters in the Model (HMM)
- Locate a user or most likely user Access Point (AP)

(3) Given: Observed movement sequence "O" over time,
Estimate: Train the model (HMM) ➔ Estimate Model Parameters