Mobility Modeling and Estimation for Delay Tolerant Unmanned Ground Vehicle networks

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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
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.
Mobility Estimation:

We must develop 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.
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.
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
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**

**UAV**

Node 1

Node 2

\[ Y_{RU} \]

\[ X_{UR} \]

\[ X_{UM} \]

**UGV Cluster Island**

Node 1

Node 2

\[ Y_{RC} \]

\[ X_{CR} \]

\[ X_{CM} \]

\[ Y_{MC} \]

\[ Y_{RC} \]

\[ Y_{RU} \]

\[ Y_{RM} \]

\[ Y_{RC} \]

**Routing Algorithms**

\[ Y_{R} = \begin{bmatrix} Y_{RU} \\ Y_{RC} \end{bmatrix} \]

**Mobility Prediction Algorithms**

\[ X_{U} = \text{Measurement Vector from UAV} = \begin{bmatrix} X_{UR} \\ X_{UM} \end{bmatrix} = \begin{bmatrix} \text{Measurements Needed for Routing} \\ \text{Measurements Needed for Mobility} \end{bmatrix} \]

\[ X_{C} = \text{Measurement Vector from Cluster} = \begin{bmatrix} X_{CR} \\ X_{CM} \end{bmatrix} = \begin{bmatrix} \text{Measurements Needed for Routing} \\ \text{Measurements Needed for Mobility} \end{bmatrix} \]
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**

\[
x_k = A(T, \alpha) x_{k-1} + B_u(T) u_k + B_w(T) w_k
\]

- \( x_k = \begin{bmatrix} x_k, \dot{x}_k, \ddot{x}_k, y_k, \dot{y}_k, \ddot{y}_k \end{bmatrix}^T \) denotes the state of the mobile node at time step \( k \)
- \( u_k = \begin{bmatrix} u_{x,k}, u_{y,k} \end{bmatrix}^T \) denotes a realistic motion discrete-time command process
- \( w_k = \begin{bmatrix} w_{x,k}, w_{y,k} \end{bmatrix}^T \) denotes a process noise, where \( w_k \sim N[0, R_w^2] \)

- \( T = \) The temporal sampling period in seconds
- \( \alpha = \) 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

\[ x_k = A(T, \alpha)x_{k-1} + B_u(T)u_k + B_w(T)w_k = \]

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

\[ \begin{align*}
    r_{k+1} &= -\alpha r_k + w_k \\
    R_{rr}(\tau) &= E\{r(t)r^T(t+\tau)\} = \sigma^2 e^{-\alpha|\tau|} I, \quad \alpha \geq 0
\end{align*} \]

The conditional probability densities of \( a_k \) 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

\[ H = \frac{\partial h}{\partial x_k} \bigg|_{x_k = \hat{x}_{k-1}} = \begin{pmatrix}
  -10\eta(x_{k,1} - a_1) \\
  \ln(10)\left( (x_{k,1} - a_1)^2 + (x_{k,4} - b_1)^2 \right) \\
  -10\eta(x_{k,1} - a_2) \\
  \ln(10)\left( (x_{k,1} - a_2)^2 + (x_{k,4} - b_2)^2 \right) \\
  -10\eta(x_{k,1} - a_3) \\
  \ln(10)\left( (x_{k,1} - a_3)^2 + (x_{k,4} - b_3)^2 \right)
\end{pmatrix} \]

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

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

- \(\mathbf{z}_k\) denotes the RSSI measurement vector (3 x 1).
- RSSI signal modeled as sum of two terms:
  - Path loss \(h\left[\mathbf{x}_k\right] = z_{0,i} - 10\eta \log_{10}\left(d_{k,i}\left[\mathbf{x}_k\right]\right)\) where \(d_{k,i}\left[\mathbf{x}_k\right] = \left[\left(x_k - a_{i,k}\right)^2 + \left(y_k - b_{i,k}\right)^2\right]^{1/2}\).
  - Rician/Rayleigh Shadow fading \(\mathbf{v}_{k,i} \sim N\left[0, \sigma_v^2\right]\).

- Shadowing can considerably degrade estimation process, but prefiltering can be used to reduce observation noise [Zaidi et Al.]
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 \( \rightarrow \) Kalman Filter
  - If Nonlinear and Gaussian \( \rightarrow \) Extended Kalman Filter
    or Unscented Kalman Filter
  - If Nonlinear and/or Non-Gaussian
    \( \rightarrow \) Sequential Monte Carlo estimator
    (Particle Filter)
The Extended Kalman Filter Uses the State-Space Model and RSSI Measurements
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

\[ e(t) = z(t) - \hat{z}(t | t - 1) \]

- 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.
Root Mean Squared State Estimation Error

The state estimation error is given by:

\[ \tilde{x}_k \triangleq x_k - \hat{x}_{k|k-1} \]

\[ E\left[ \tilde{x}_k^T \tilde{x}_k \right] = MSE\left( \tilde{x}_k \right) \]

\[ \sigma_{\tilde{x}} \triangleq \sqrt{\text{var}\left( \tilde{x}_k \right)} \]

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

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

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

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

Hypothesis Test

\[
\frac{\gamma(l)}{\tau} < \frac{\gamma(l)}{\tau}
\]

\(\tau = \text{Decision Threshold}\)
Example: How to Compute the Scalar WSSR for a Scalar Innovations Sequence

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

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

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

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

- The Fisher Information Matrix using likelihoods lambda

\[
J_k = E_{\hat{x}_k} \left\{ \left[ \nabla_{\hat{x}_k} \lambda(\frac{x_k}{\hat{x}_k}) \right] \left[ \nabla_{\hat{x}_k} \lambda(\frac{x_k}{\hat{x}_k}) \right]' \right\}_{\hat{x}_k = x_0}, \quad \lambda(\frac{x_k}{\hat{x}_k}) = \ln p(\frac{x^*}{\hat{x}_k})
\]

- The PCRLB for this problem is

\[
PCRLB = \sqrt{P_{k|k}(1,1) + P_{k|k}(4,4)}.
\]
Simulation Experiment and Performance Measurement

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## Initial State and State Covariance Estimates

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial state covariance estimate</td>
<td>$\begin{pmatrix} 400^2 &amp; 0 &amp; 0 &amp; 0 &amp; 0 &amp; 0 &amp; 0 \ 0 &amp; 15^2 &amp; 0 &amp; 0 &amp; 0 &amp; 0 &amp; 0 \ 0 &amp; 0 &amp; 5^2 &amp; 0 &amp; 0 &amp; 0 &amp; 0 \ 0 &amp; 0 &amp; 0 &amp; 400^2 &amp; 0 &amp; 0 &amp; 0 \ 0 &amp; 0 &amp; 0 &amp; 0 &amp; 15^2 &amp; 0 &amp; 0 \ 0 &amp; 0 &amp; 0 &amp; 0 &amp; 0 &amp; 5^2 &amp; 0 \end{pmatrix}$</td>
</tr>
<tr>
<td>Initial state estimate</td>
<td>$\begin{pmatrix} 3400 \ 5 \ 0 \ 8700 \ 8 \ 0 \end{pmatrix}$</td>
</tr>
</tbody>
</table>
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

\[ X_{dot\_x}(t) \]

\[ X_{dot\_y}(t) \]
Measurement Noise Vector $v(k)$ (For 3 Base Stations)

$v_k \rightarrow N[0, 8I]$

$\pm 2\sigma_v = \pm 8$
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 $\text{Xtilda}(k) = x(k) - \text{xhat}(k|k)$ and its “Two Sigma Error Bounds” vs. Time
Innovations Vector $e(t)$ and “2 Sigma Error Bounds”

$$e(k) = z(k) - \hat{z}(k|k-1)$$

![Graphs showing Innovations $E = e(t)$ and Two Sigma Bounds vs. Time with no points outside bounds, indicating a percent of 0.3.](image)

- $E_1(t)$
- $E_2(t)$
- $E_3(t)$

Time in Seconds (No. Pts. Outside Bound = 2 (Percent = 0.3))
Statistical Whiteness Test on the Innovations
\[ e(k) = z(k) - \hat{z}(k|k-1) \]
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

Computed by Ensemble Averaging
Over 100 Realizations of the Stochastic Processes
Red: Speed RMS (x and y combined)  
Blue: PCRLB on the Speed RMS  

Computed by Ensemble Averaging 
Over 100 Realizations of the Stochastic Processes
WSSR (Weighted Sum Squared Residuals) Are Well Below the Threshold (Red), So the EKF is Well Tuned

The WSSR Threshold is the Red Line
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
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
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: \( a(t) \)
- Velocity Vector: \( v(t) \)
- Position Vector: \( p(t) \)
- RSSI Information: \( r(t) \)

\[
\begin{bmatrix}
X_{Node} \\
\end{bmatrix}
\begin{bmatrix}
\hat{a}(t) \\
\hat{v}(t) \\
\hat{p}(t) \\
\hat{r}(t)
\end{bmatrix}
\]

RSSI = Received Signal Strength Indicator
⇒ Power of the Signal Received at the Antenna

\[
X_C = \text{Measurement Vector from Cluster} = \begin{bmatrix}
X_{CR} \\
X_{CM}
\end{bmatrix} = \begin{bmatrix}
\text{Measurements Needed for Routing} \\
\text{Measurements Needed for Mobility}
\end{bmatrix}
\]
Measurements from the UAV

\[
\begin{align*}
\text{Acceleration Vector} &= a(t) \\
\text{Velocity Vector} &= v(t) \\
\text{Position Vector} &= p(t)
\end{align*}
\]

\[
X_U = \begin{bmatrix}
a(t) \\
v(t) \\
p(t)
\end{bmatrix}
\]

\[
X_U = \text{Measurement Vector from UAV} = \begin{bmatrix}
X_{UR} \\
X_{UM}
\end{bmatrix} = \begin{bmatrix}
\text{Measurements Needed for Routing} \\
\text{Measurements Needed for Mobility}
\end{bmatrix}
\]
Outputs from the Routing Algorithms

Routing Algorithms

\[ X_{UR} \quad \text{Routing Algorithms} \quad Y_R = \begin{bmatrix} Y_{RU} \\ Y_{RC} \end{bmatrix} \quad Y_{CR} \]

End-to-End Path Between Two Nodes that are Communicating within the Cluster
Our Focus is on the Mobility Prediction Algorithms

Predicted Position vs. Time for a Particular UGV Node in the Cluster

Mobility Prediction Algorithms

$X_{UM}$

$X_{CM}$

$Y_M$
UAV and UGV Information Flow

\[ \begin{align*}
X_U &= \text{Measurement Vector from UAV} = \begin{bmatrix} X_{UR} \\ X_{UM} \end{bmatrix} = \begin{bmatrix} \text{Measurements Needed for Routing} \\ \text{Measurements Needed for Mobility} \end{bmatrix} \\
X_C &= \text{Measurement Vector from Cluster} = \begin{bmatrix} X_{CR} \\ X_{CM} \end{bmatrix} = \begin{bmatrix} \text{Measurements Needed for Routing} \\ \text{Measurements Needed for Mobility} \end{bmatrix}
\end{align*} \]
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
• **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

**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:

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

Where:

\(q^{-1}\) = Delay Operator

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

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

\(C(q) = 1 + c_1 q^{-1} + c_2 q^{-2} \ldots + c_{N_c} q^{-N_c}\)

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

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

\(e(t)\) = Exogenous Input

\(= A\) White Noise Sequence

\(u(t)\) = Input

\(y(t)\) = Output
My Focus: Mobility Modeling and Prediction

- We need Signal Processing and Control
- Models are probabilistic and dynamic: 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 \( \lambda \)

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) \( \Rightarrow \) Estimate Model Parameters