A Multi-Model Filter for Mobile Terminal Location Tracking

by

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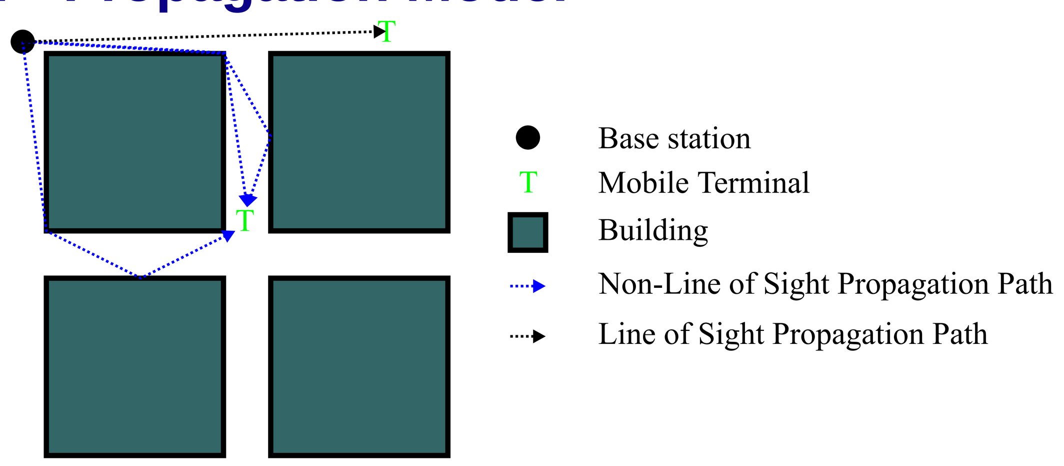
1 Introduction

- Reasons for location technologies:
  - Resource allocation, location sensitive browsing, emergency communications.
- Many measurement types proposed:
  - Received Signal Strength (RSS), Angle of Arrival (AoA), Time of Arrival (ToA), Time Difference of Arrival (TDoA)
  - All methods have errors in location estimation.
- Filtering is proposed to reduce estimation errors.
  - Performance of filter dependent on model of dynamic and measurement process.
- Propose a mobile terminal model which is
  - Based on an accurate model of mobile terminal motion.
  - Model parameters based on real world measurements.

2 Propagation and Measurement Model

2.1 Propagation Model



- Use ToA measurements
- Consider effects of:
  - Line of sight and non line of sight propagation
  - Multipath propagation

2.2 Measurement model

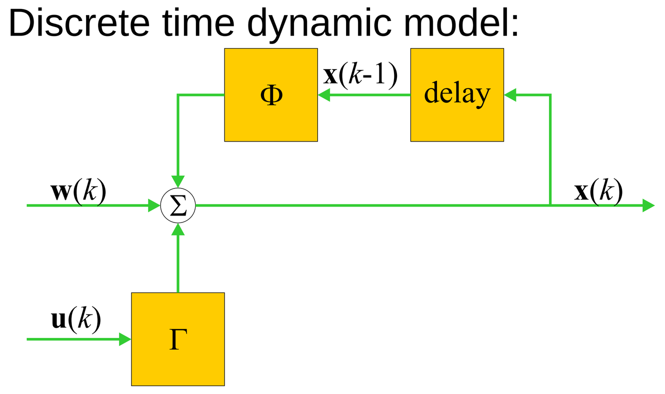
- Zero memory estimation creates a linear pseudo-measurement:

$$\mathbf{y}(k) = \mathbf{H}\mathbf{x}(k) + \mathbf{v}(k)$$

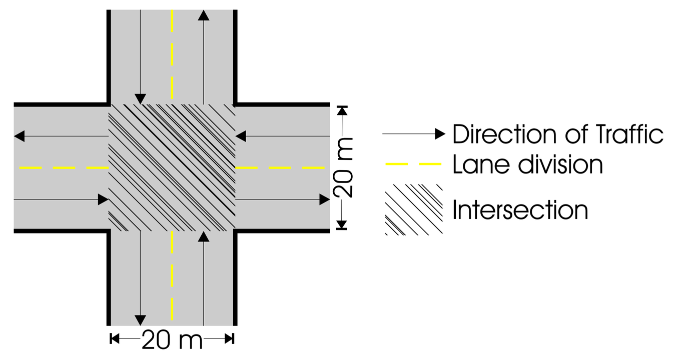
- $\mathbf{y}(k)$ is estimated location for k calculated from $\mathbf{z}(k)$
  - Non-parametric estimation method used.
  - Survey points characterize propagation environment.
  - Robust to multipath and non line of sight propagation.
- $\mathbf{H}$ is the measurement matrix
- $\mathbf{x}(k)$ is the location state of the mobile terminal at time k
- $\mathbf{v}(k)$ is the measurement noise at time k
- $\mathbf{R}(k)$ is the covariance of $\mathbf{v}(k)$

2.3 Motion Model

- Discrete time dynamic model:



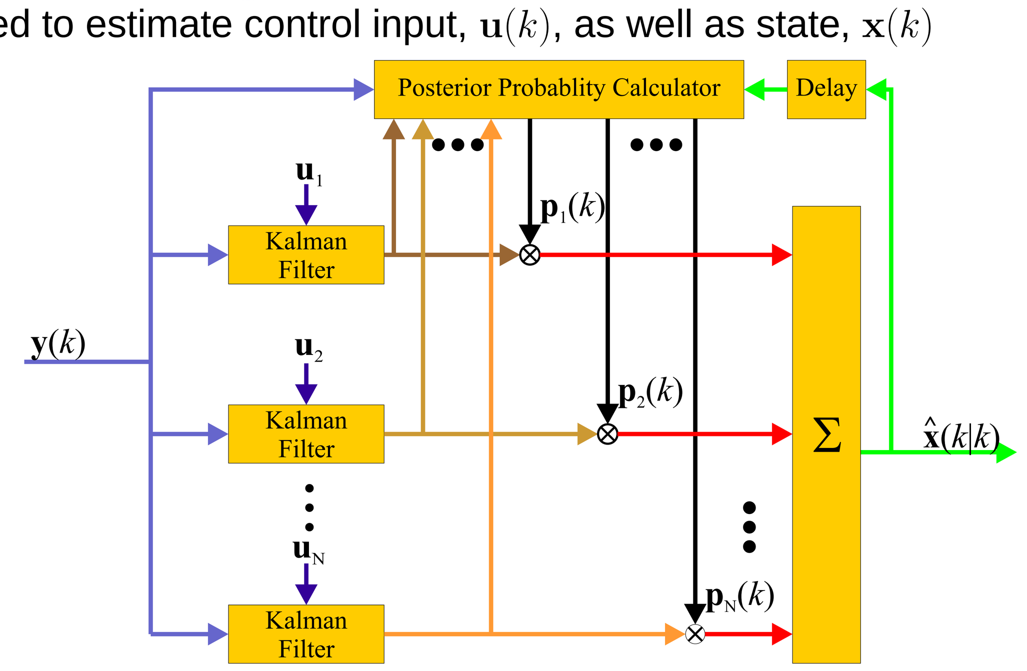
- $\mathbf{x}(k)$ is the location state of mobile terminal at time k
- $\mathbf{\Phi}$ is the state transition matrix
- $\mathbf{\Gamma}$ describes influence of control input on state
- $\mathbf{u}(k)$ is user control input at time k
- $\mathbf{w}(k)$ is Gaussian random process noise with covariance $\mathbf{Q}$



- $\mathbf{u}(k)$ changes most often when user in intersection.
- $\mathbf{u}(k)$ usually invariant when user not in intersection.
- Discrete set of possible control inputs:
  - $\mathbf{u}(k) \in \{\mathbf{u}_1, \mathbf{u}_2, ..., \mathbf{u}_N\}$
  - Control inputs match direction of streets.

3 Filtering and State Estimation

- Need to estimate control input, $\mathbf{u}(k)$, as well as state, $\mathbf{x}(k)$



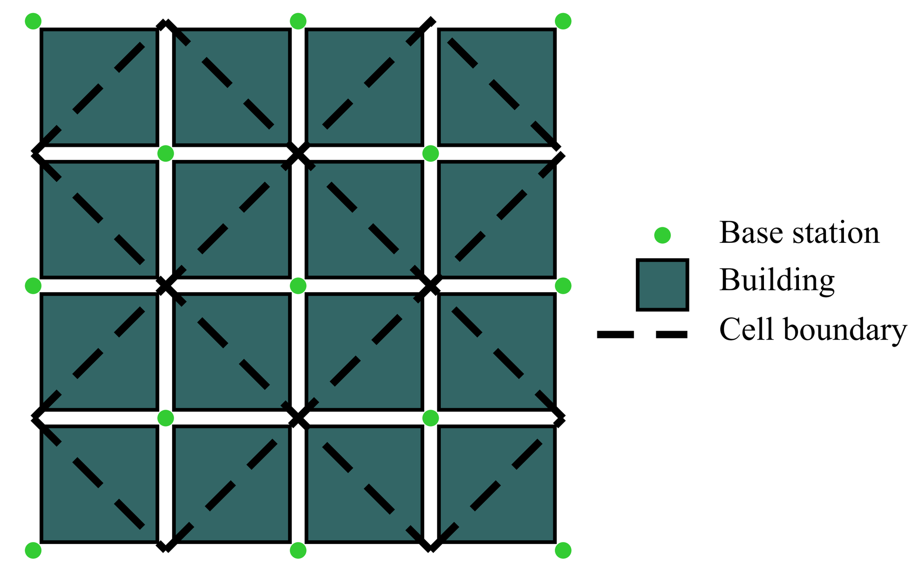
- Bank of Kalman filters
  - Final estimate for $\mathbf{x}(k)$ is a weighted average of Kalman filter outputs.
  - Each Kalman filter matched to possible control input.
  - Weights updated using measurement $\mathbf{y}(k)$, old weights, and control input transition probabilities.
  - Control input transitions calculated from estimate of $\mathbf{x}(k-1)$

3.1 Estimation of Control Input

- Control input process modeled as Markov-one process given location
  - Transition probability of control input is a function of current location and current control input.
    - e.g. Transitions more likely in intersections.
- Increasing convergence speed of Kalman filters:
  - $\mathbf{Q} = \mathbf{Q}_{model} + \mathbf{\Gamma} Q_u \mathbf{\Gamma}^T$
  - $\mathbf{Q}_{model}$ is covariance of $\mathbf{w}(k)$ from dynamic model
  - Trade off in selection of Q_u:
    - High value gives fast convergence with larger final error
    - Low value gives slow convergence with lower final error
    - Optimal value function of probability of turning at intersections.

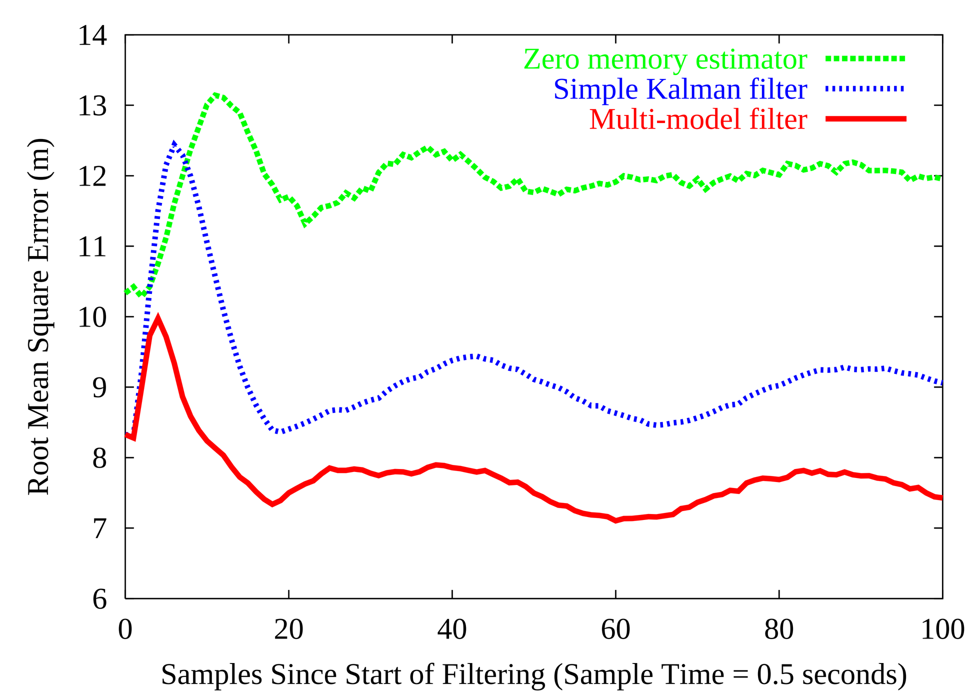
4 Results

- Simulated urban environment

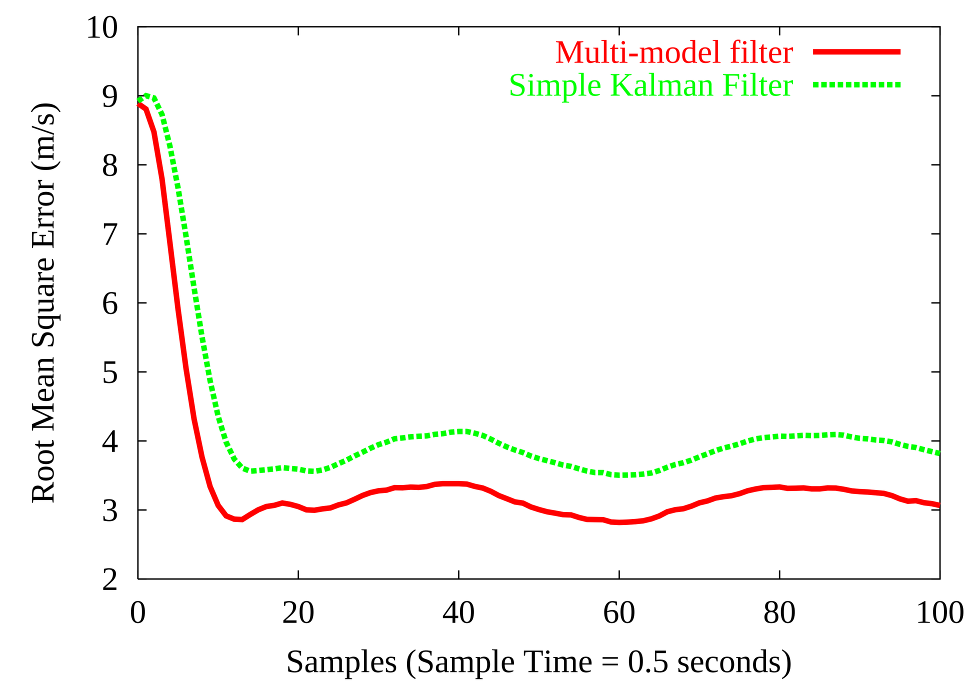


  - Realistic propagation model
  - Realistic base station selection
  - Maneuvering mobile terminal
- New filter compared with application of single Kalman filter
  - Simple Kalman filter assumes $\mathbf{u}(k)$ is a Gaussian random process.

Location Error Comparison

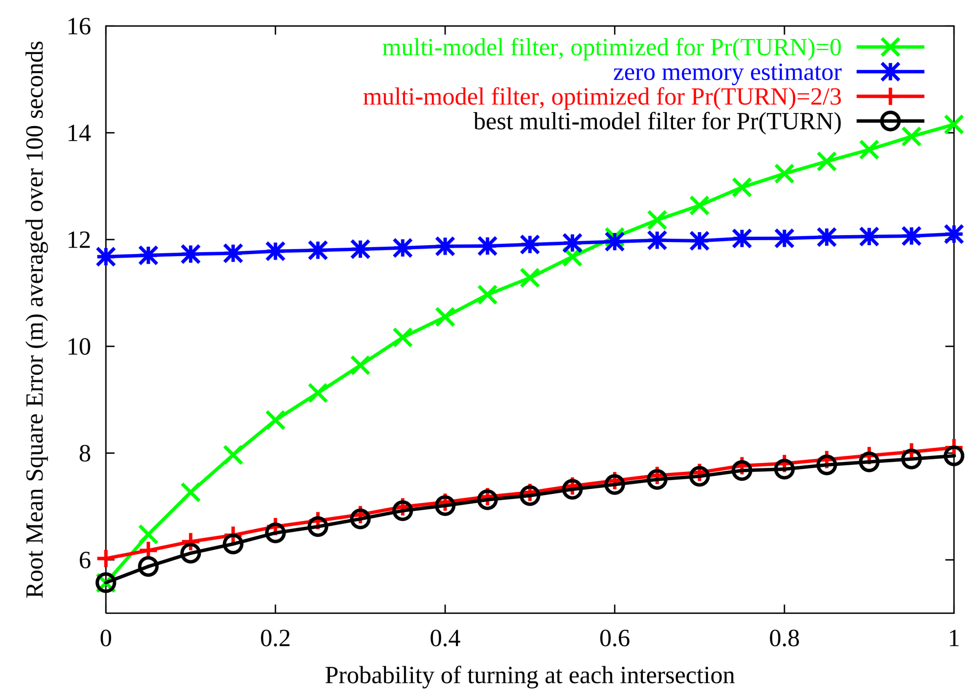


Velocity Error Comparison



- Results of comparison:
  - New filter has lower error.
  - New filter converges faster than single Kalman filter
- Test of Filter Robustness
  - Mobile's probability of turning at each intersection varied
  - New filter optimized for different turning probabilities tested

Robustness of Filter



5 Conclusions

1. New multi-model filter increases accuracy of mobile terminal location.
2. New filter is robust to changes in motion model.