

# State Estimation and Motion Tracking for Spatially Diverse VLC Networks

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# Outline

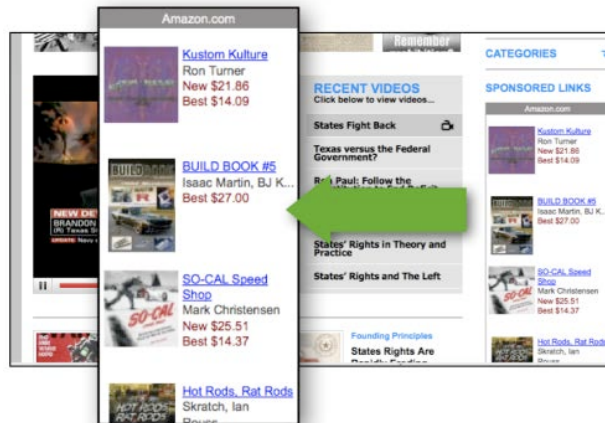
- Motivation
- Visible Light Communication
- Kalman Filtering
- System Model
- Results and Conclusions

## Consider This...

We live in a society where access to information is ubiquitous.



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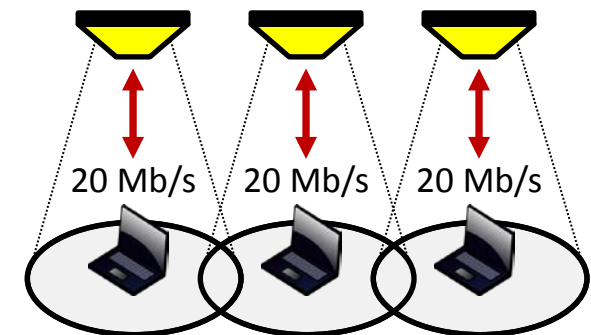
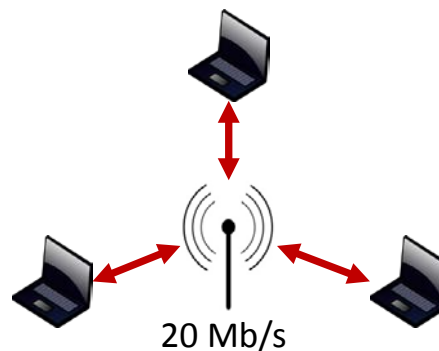
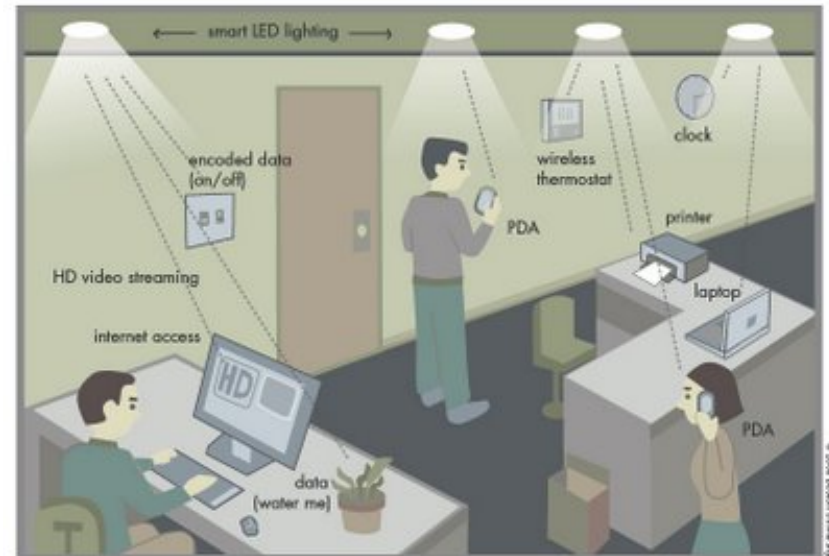
# Motivation: *Indoor Localization*

- Personalized local information
  - Augmented knowledge of surroundings
  - Targeted advertisement
  - Indoor navigation
- Communication Systems
  - Handover in VLC or heterogeneous networks
  - Traffic routing based on dynamic traffic patterns
- We propose a novel state estimation model
  - Approximates user location and motion path
  - Predicts future state through use of recursive estimation

High aggregate throughput...  
Data is everywhere!

## Visible Light Communication (VLC)

- Intensity Modulation / Direct Detection (IM/DD)
- Dual Purpose System
  - Fully functional lighting system
  - Wireless data communication
- Benefits
  - Dual use
  - Secure connections
  - Unregulated spectrum
  - *Signal Directionality*
  - High bandwidth density



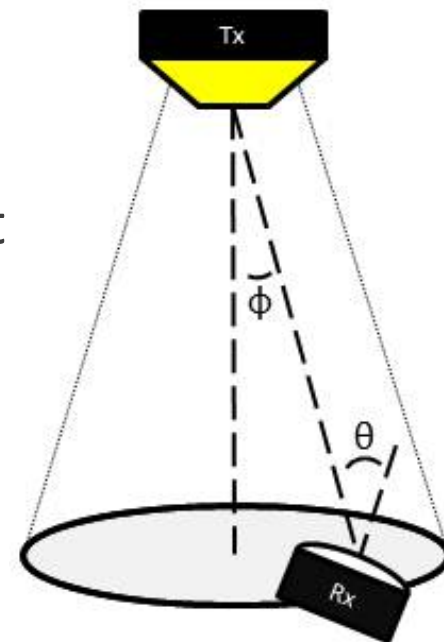
## VLC Channel Model

- Transmitted power,  $P_t$ , distance,  $D$ , receiver area,  $A_r$ , and angle at the transmitter and receiver account for LOS received power.

$$P_r = \frac{P_t T(\phi) A_r g(\theta)}{D^2}$$

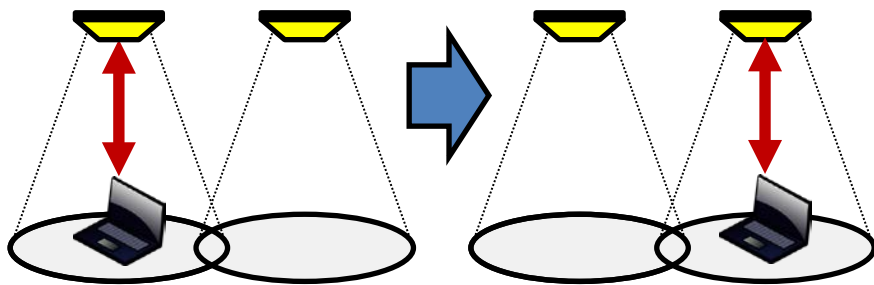
- LEDs and photodiodes have an angle dependent gain typically modeled as

$$T(\phi) = \frac{n+1}{2\pi} \cos^n(\phi) \quad g(\theta) = \cos(\theta)$$

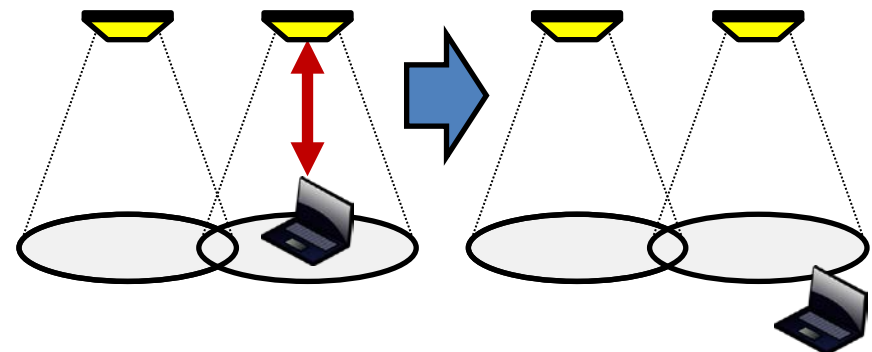


# VLC Network Considerations

- Fast and accurate handover protocols are necessary to maintain connectivity throughout the environment.
  - HHO: Transfer between VLC channels
  - VHO: Transfer between media (e.g. VLC to RF)
- RSI allows for basic handover methods, but motion tracking provides an opportunity for predictive methods.



Horizontal Handover (HHO)



Vertical Handover (VHO)

# Kalman Filtering

- Discrete time linear state models can be employed to describe the behavior of dynamic systems.

$$\mathbf{x}[t + 1] = \mathbf{A}\mathbf{x}[t] + \mathbf{G}\mathbf{w}[t] \qquad \mathbf{y}[t] = \mathbf{C}\mathbf{x}[t] + \mathbf{H}\mathbf{v}[t]$$

- Kalman Filters observe a series of noisy measurements, then recursively estimate the system state and predict the next state.
  1. Initialization
  2. Prediction
  3. Measurement
  4. Update
- Since measurement in our system is non-linear, we observe extensions of the basic KF.
  - Extended Kalman Filter (EKF)
  - Unscented Transform (UT)

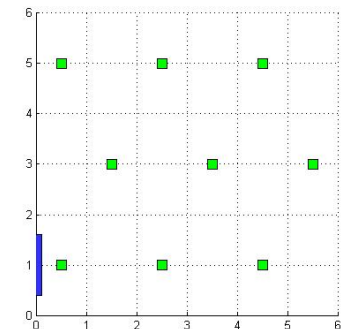
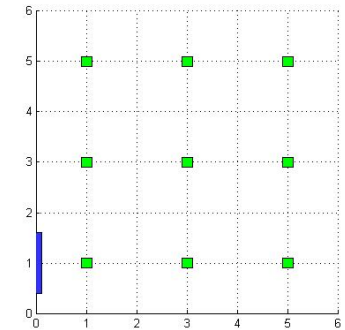
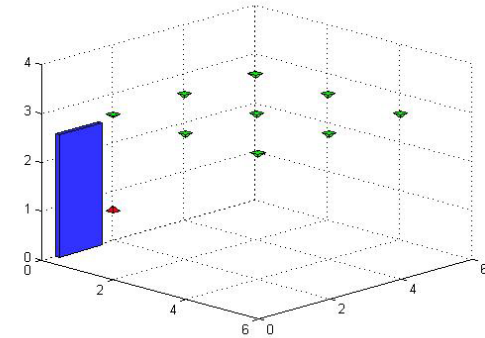


## System Model

- Empty 6m X 6m X 4m room with grid or cell layout.
- New user location is normally distributed with expected value below a hotspot.
- Users move with zero mean acceleration in the  $x$  and  $y$  direction.
- Observe a linear state model,  $\mathbf{x}[t]$ , with transition matrix,  $\mathbf{A}$ , and nonlinear measurement,  $\mathbf{y}$ .

$$\mathbf{x}[t+1] = \mathbf{A}\mathbf{x}[t] + \mathbf{w}[t] \quad \mathbf{y}[t] = h[\mathbf{x}[t], t] + \mathbf{v}[t]$$

- Process noise,  $\mathbf{w}$ , and measurement noise,  $\mathbf{v}$ , are independent, zero-mean, Gaussian white noise with covariance matrices  $\mathbf{Q}$  and  $\mathbf{R}$ , respectively.



## System Model – Scenario I

- Receiver is directed perpendicular to floor, such that  $\phi = \theta$ .
- State represents position and velocity in  $x$  and  $y$ .
- Measurement observes signal power from the set of transmitters.

$$\mathbf{x} = [x, V_x, y, V_y]' \quad \mathbf{y} = [P_{r,1j}, P_{r,2j}, \dots, P_{r,9j}]' + \mathbf{v}[t]$$

$$\mathbf{A}_I = \begin{bmatrix} 1 & dt & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & dt \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

- $P_{r,1j}$  is dependent on  $\phi_{ij}$ ,  $\theta_{ij}$ , and  $D_{ij}$ .

$$D_{ij}^2 = (X_i - x)^2 + (Y_i - y)^2 + (Z_i - z)^2$$

$$\phi_{ij} = \theta_{ij} = \arctan\left(\frac{\sqrt{(X_i - x)^2 + (Y_i - y)^2}}{Z_i - z}\right)$$

$$\mathbf{Q}_I = q \cdot \begin{bmatrix} \frac{dt^3}{3} & \frac{dt^2}{2} & 0 & 0 \\ \frac{dt^2}{2} & dt & 0 & 0 \\ 0 & 0 & \frac{dt^3}{3} & \frac{dt^2}{2} \\ 0 & 0 & \frac{dt^2}{2} & dt \end{bmatrix}$$

$$\mathbf{R}_I = r_{sig} \cdot \mathbf{I}_{9 \times 9}$$

## System Model – Scenario II

- Incorporate device rotation in the state model.

$$\mathbf{x} = [x, V_x, y, V_y, \theta_{el}, \theta_{az}]'$$

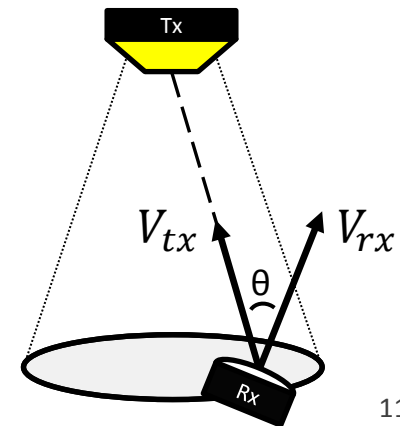
$$\mathbf{A}_{II} = \begin{bmatrix} A_I & \bar{0} \\ \bar{0} & \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \end{bmatrix} \quad \mathbf{Q}_{II} = \begin{bmatrix} Q_I & \bar{0} \\ \bar{0} & \begin{bmatrix} (q_\theta)dt & 0 \\ 0 & (q_\theta)dt \end{bmatrix} \end{bmatrix}$$

- The acceptance angle,  $\theta_{ij}$ , is now dependent on  $\theta_{el}$  and  $\theta_{az}$ .

$$\mathbf{V}_{rx} = \{\cos(\theta_{el}) \cdot \sin(\theta_{az}), \sin(\theta_{el}) \cdot \sin(\theta_{az}), \cos(\theta_{az})\}$$

$$\mathbf{V}_{tx,i} = \{(X_i - x), (Y_i - y), (Z_i - z)\}$$

$$\cos(\theta_{ij}) = \frac{\mathbf{V}_{rx} \cdot \mathbf{V}_{tx,i}}{|\mathbf{V}_{rx}| |\mathbf{V}_{tx,i}|}$$



## System Model – Scenario III

- Additional measurements for  $\theta_{el}$  and  $\theta_{az}$  are included.

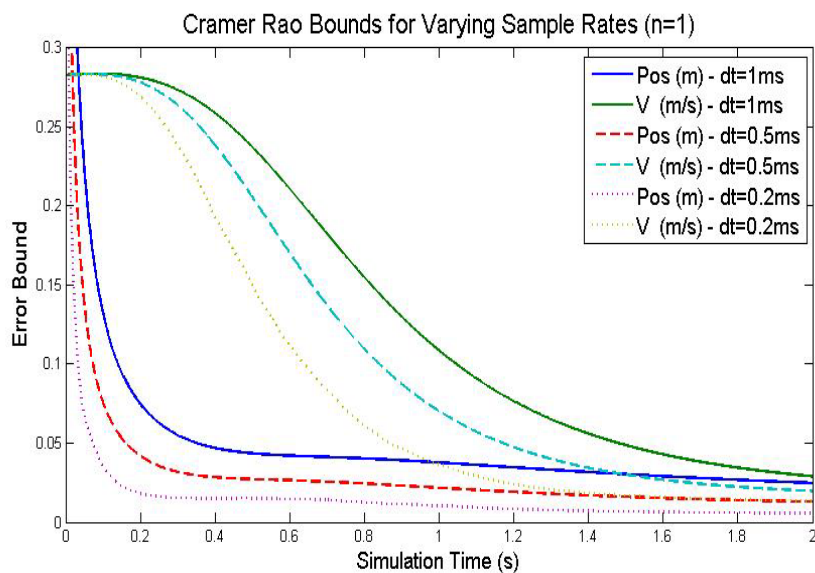
$$\mathbf{y} = [P_{r,1j}, P_{r,2j}, \dots, P_{r,9j}, \theta_{el}, \theta_{az}]' + \mathbf{v}[t]$$

$$\mathbf{R}_{III} = \begin{bmatrix} \mathbf{R}_I & \bar{\mathbf{0}} \\ \bar{\mathbf{0}} & r_\theta \cdot \mathbf{I}_{2 \times 2} \end{bmatrix}$$

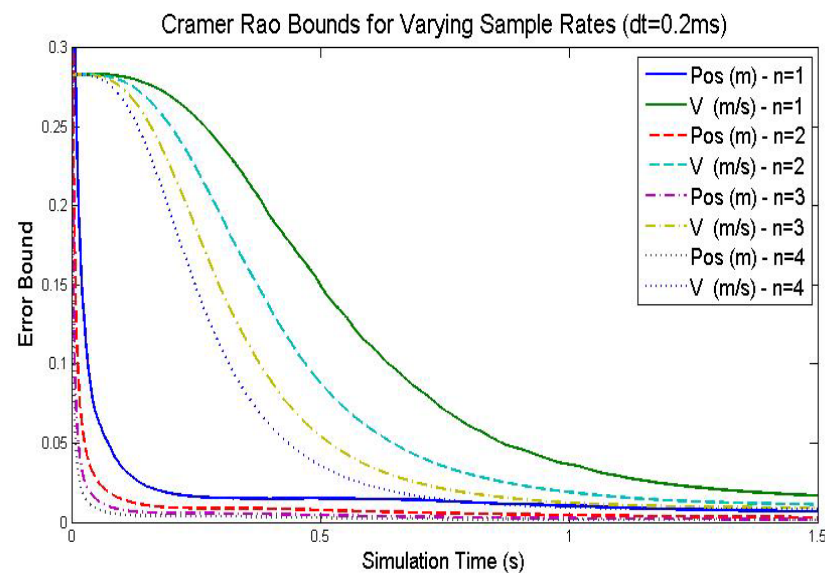
- We aim to show that additional sensors (e.g. accelerometers or gyroscopes) can improve performance in a realistic scenario.

## Results

- We first observe Cramer Rao Bounds (CRB) for the simulated data.



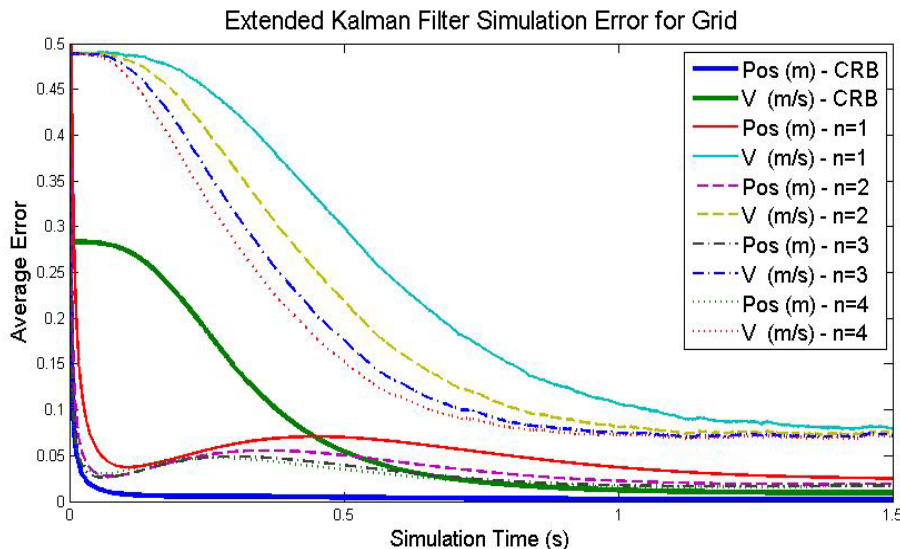
**Cramer Rao Bounds for multiple sampling rates**



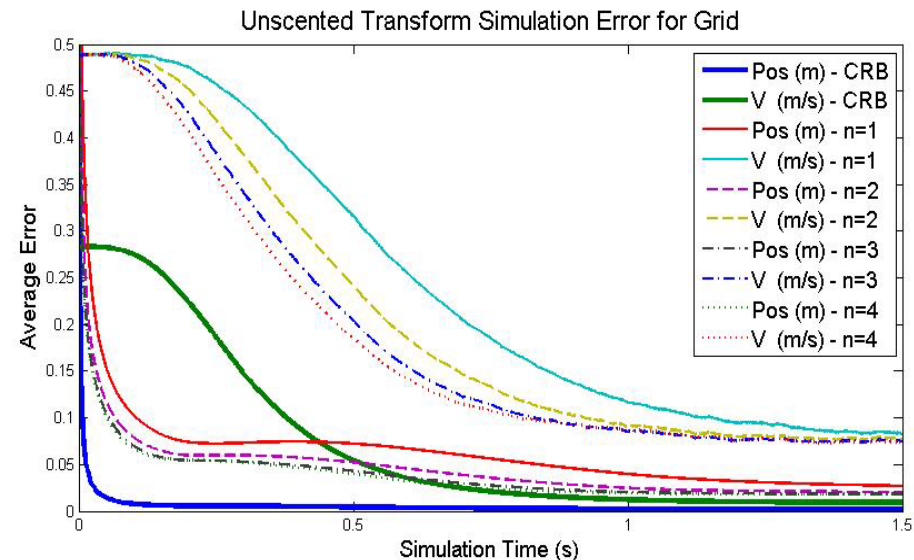
**Cramer Rao Bounds for multiple transmitter orders**

## Results

- We next compare estimations to the actual position and velocity.



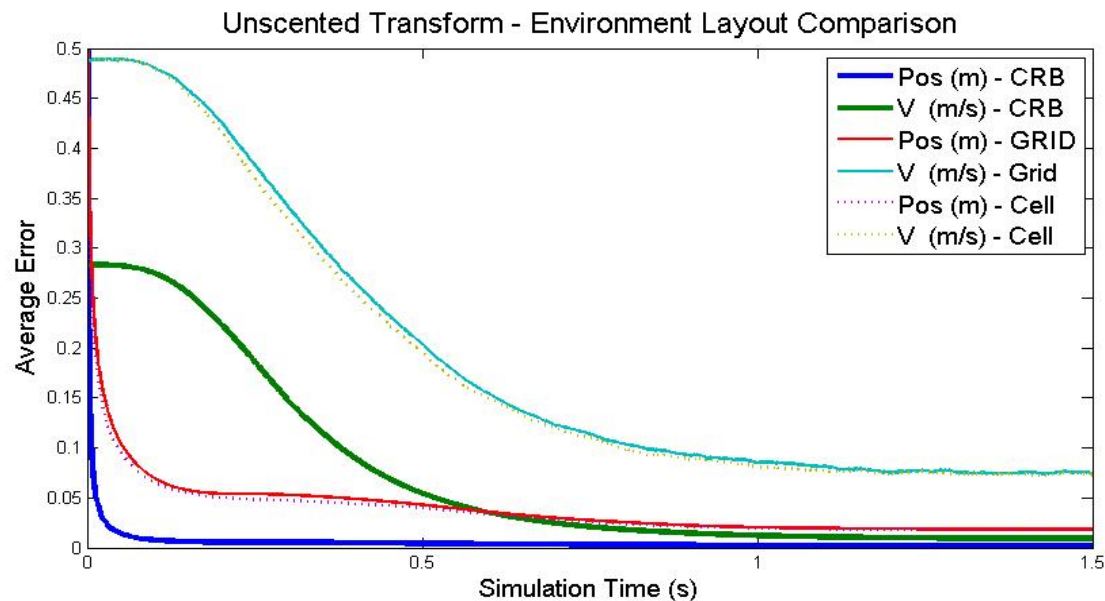
Simulation results for the Extended Kalman Filter



Simulation results for the Unscented Filter

## Results

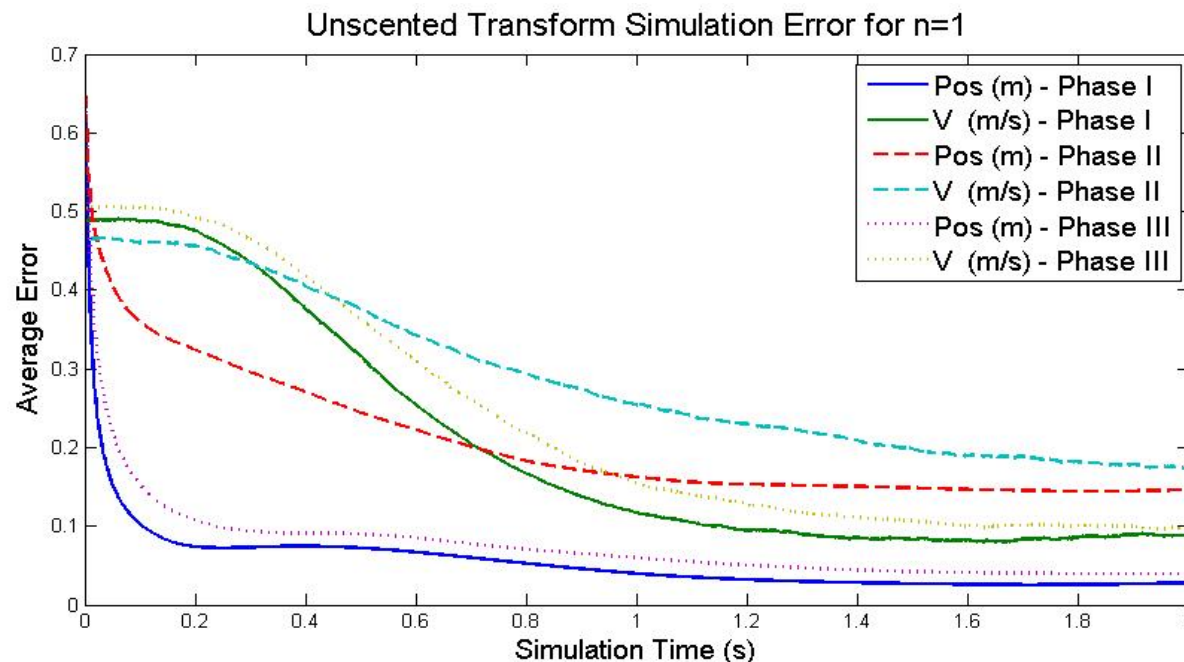
- Cellular and grid layouts show similar performance; however the initial distribution in the cellular scenario was not located directly below a transmitter.



Simulation results comparing grid and cellular layouts

## Results

- Scenario II shows a significant performance loss over Scenario I; however the additional sensors in Scenario III provide similar performance to that of Scenario I.



Simulation results comparing scenarios I, II, and III



## Conclusions

- We have provided a novel state estimation model leveraging the lighting infrastructure to approximate user location and motion under realistic conditions.
- Simulation results on an empty room show position and velocity results with average error of 5cm and 10cm/s, respectively.
- We recognize that additional complexities occur due to dynamic signal conditions from obstructions and signal reflections.
  - Non-ideal luminaire output
  - Receiver Optics
  - Multipath Signals
  - User obstruction
- Results are applicable for positioning systems and asset tracking as well as assisted handover or beam steering for indoor VLC networks

# Questions



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# STATE ESTIMATION AND MOTION TRACKING FOR SPATIALLY DIVERSE VLC NETWORKS

**BOSTON**  
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## Table of Parameters

Parameter	Phase I	Phase II / III
<b>System Parameters</b>		
$P_t$ (W)	5	5
$A_r$ (mm <sup>2</sup> )	300	300
$dt$ (ms)	0.2, 0.5, 1	0.2
$n$	1,2,3,4	1
<b>Initial Expectations</b>		
$E[x,y]$ (m)	[0.99, 0.99]	[0.99, 0.99]
$E[V_x, V_y]$ (m/s)	[0.8, 0.8]	[0.8, 0.8]
$E[\theta_{el}, \theta_{az}]$ (°)	-	[0,0]
$\Sigma[x,y]$ (m)	[0.5,0.5]	[0.5,0.5]
$\Sigma[V_x, V_y]$ (m/s)	[0.2,0.2]	[0.2,0.2]
$\Sigma[\theta_{el}, \theta_{az}]$ (°)	-	$[\frac{\pi}{180}, \frac{\pi}{4}]$
<b>Noise Parameters</b>		
$r_{sig}$	$3.5 \cdot 10^{-8}$	$3.5 \cdot 10^{-8}$
$r_{\theta}$	-	$\frac{\pi}{360}$
$q$	$10^{-2}$	$10^{-2}$
$q_{\theta}$	-	$\frac{\pi}{360}$

## Kalman Filter Details

- **Prediction**
$$\begin{aligned}\mathbf{x}_{t+1|t} &= \mathbf{A}\mathbf{x}_{t|t} + \mathbf{B}u[t] + \mathbf{G}E\{w[t]\} \\ \Sigma_{t+1|t} &= \mathbf{A}\Sigma_{t|t}\mathbf{A}^T + \mathbf{G}\mathbf{Q}\mathbf{G}^T \\ \mathbf{y}_{t+1|t} &= \mathbf{C}\mathbf{x}_{t|t} + \mathbf{D}u[t] + \mathbf{H}E\{v[t]\}\end{aligned}$$

- **Estimation**
$$\begin{aligned}\mathbf{x}_{t+1|t+1} &= \mathbf{x}_{t+1|t} + \mathbf{K}_{t+1}\mathbf{v}_{t+1} \\ \Sigma_{t+1|t+1} &= [\mathbf{I} - \mathbf{C}\mathbf{K}_{t+1}]\Sigma_{t+1|t}\end{aligned}$$

- **Innovations**

$$\mathbf{v}_{t+1} = \mathbf{y}_{t+1} - \mathbf{y}_{t+1|t}$$

- **Kalman Gain**

$$\mathbf{K}_{t+1} = \Sigma_{t+1|t}\mathbf{C}^T[\mathbf{C}\Sigma_{t+1|t}\mathbf{C}^T + \mathbf{R}]^{-1}$$