Slide 3/7

## BALL TRACKING WITH THE KALMAN FILTER

Ball physical model:

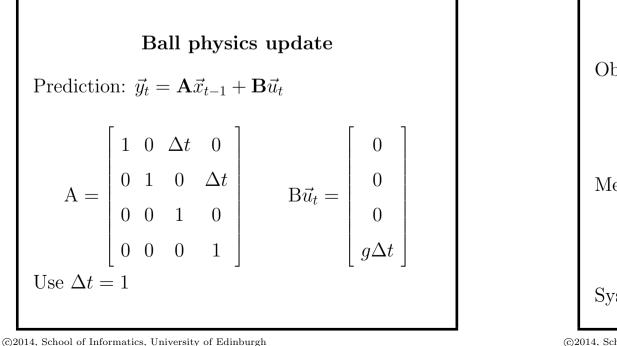
Position:  $\vec{p_t} = (col_t, row_t)'$ Velocity:  $\vec{v}_t = (velcol_t, velrow_t)'$ Position update:  $\vec{p}_t = \vec{p}_{t-1} + \vec{v}_{t-1}\Delta t$ Velocity update:  $\vec{v}_t = \vec{v}_{t-1} + \vec{a}_{t-1}\Delta t$ Acceleration (gravity down):  $\vec{a}_t = (0, g)'$ 

State vector:  $\vec{x}_t = (col_t, row_t, velcol_t, velrow_t)'$ Initial state vector: random

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Slide 4/7



Rest of model  
Observation process:  

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$
Measurement noise:  

$$R = \begin{bmatrix} 0.285 & 0.005 \\ 0.005 & 0.046 \end{bmatrix}$$
System noise: 
$$Q = 0.01 \times I$$

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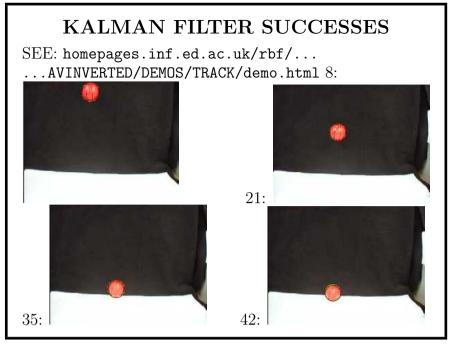
Ball Tracking with Kalman Filter

**Ball Tracking Example** 

Robert B. Fisher

School of Informatics

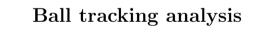
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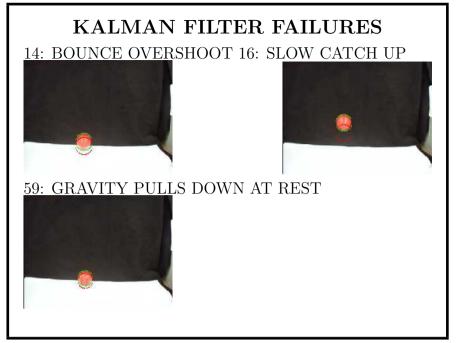
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Ball Tracking with Kalman Filter

Slide 7/7



- KF smooths noisy observations (not so noisy here) to give better estimates
- Could also estimate ball radius
- Could also plot boundary of 95% likelihood of ball position - grows when fit is bad
- Dynamic model doesn't work at bounce & stop



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