



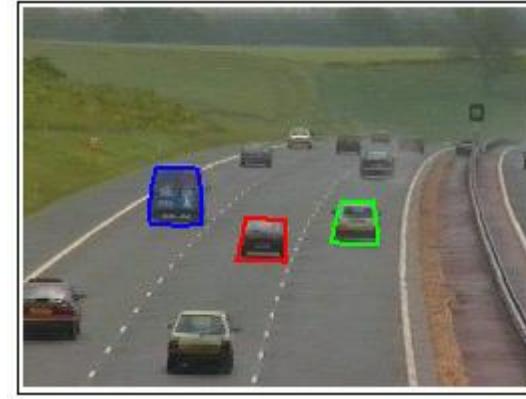
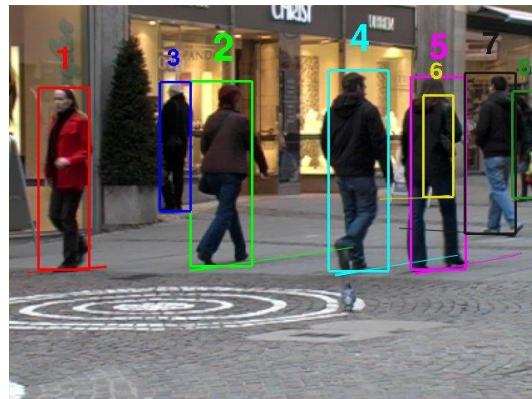
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# CMP9135M - Computer Vision **Visual Tracking II**

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# Recap of last week

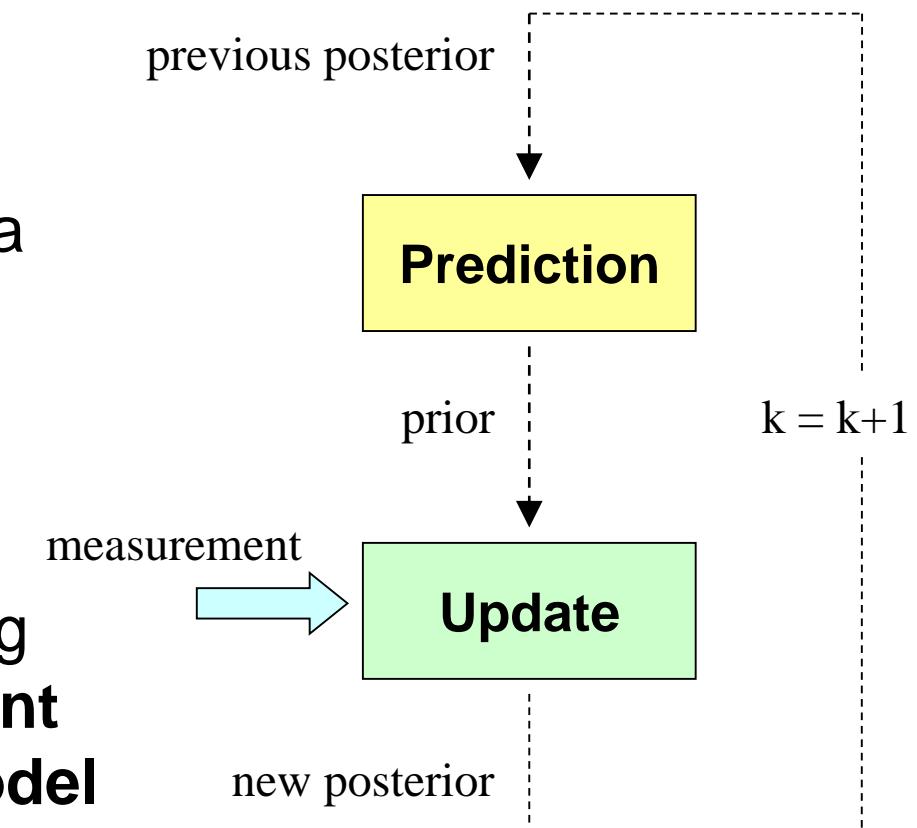
- Motion models
- Observation models
- Recursive Bayesian Estimation



# Bayesian Estimation

- Recursive estimation with two main steps:

- Prediction – to compute a prior probability with the **motion model**
- Update – to compute a posterior probability using the **current measurement** and the **observation model**



# Kalman Filter

- In this case, the prediction-update cycle of the Kalman filter becomes a simple sequence of matrix operations as follows

Prediction

$$\begin{aligned}\hat{\mathbf{x}}_k &= \mathbf{F} \mathbf{x}_{k-1} \\ \hat{\mathbf{P}}_k &= \mathbf{F} \mathbf{P}_{k-1} \mathbf{F}^T + \mathbf{Q}\end{aligned}$$

Update

$$\begin{aligned}\mathbf{x}_k &= \hat{\mathbf{x}}_k + \mathbf{K}_k (\mathbf{z}_k - \hat{\mathbf{z}}_k) \\ \mathbf{P}_k &= \hat{\mathbf{P}}_k - \mathbf{K}_k \mathbf{S}_k \mathbf{K}_k^T\end{aligned}$$

- where

$$\hat{\mathbf{z}}_k = \mathbf{H} \hat{\mathbf{x}}_k \quad \text{and} \quad \mathbf{S}_k = \mathbf{H} \hat{\mathbf{P}}_k \mathbf{H}^T + \mathbf{R} \quad \text{and} \quad \mathbf{K}_k = \hat{\mathbf{P}}_k \mathbf{H}^T \mathbf{S}_k^{-1}$$



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# KF Prediction

## Prediction

$$\hat{\mathbf{x}}_k = \mathbf{F} \mathbf{x}_{k-1}$$

$$\hat{\mathbf{P}}_k = \mathbf{F} \mathbf{P}_{k-1} \mathbf{F}^T + \mathbf{Q}$$

- $\mathbf{x}$  = state vector ( $\hat{\cdot}$  means “predicted”)
- $\mathbf{F}$  = matrix of the motion model
- $\mathbf{Q}$  = matrix of the motion noise
- $\mathbf{P}$  = covariance matrix of  $\mathbf{x}$

# KF Prediction

- Example: Brownian motion

$$\begin{cases} x_k &= x_{k-1} + n_{k-1}^x \\ y_k &= y_{k-1} + n_{k-1}^y \end{cases}$$

- in this case

$$\mathbf{x}_k = \begin{bmatrix} x_k \\ y_k \end{bmatrix} \quad \mathbf{F} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$
$$\mathbf{Q} = \begin{bmatrix} \sigma_{nx}^2 & 0 \\ 0 & \sigma_{ny}^2 \end{bmatrix}$$

- $\mathbf{P}$  is computed from  $\mathbf{F}$  and  $\mathbf{Q}$

# KF Prediction

- Example: Constant Velocity model

$$\begin{cases} x_k = x_{k-1} + \dot{x}_{k-1} \Delta t_k + n_{k-1}^x \\ \dot{x}_k = \dot{x}_{k-1} + n_{k-1}^{\dot{x}} \\ y_k = y_{k-1} + \dot{y}_{k-1} \Delta t_k + n_{k-1}^y \\ \dot{y}_k = \dot{y}_{k-1} + n_{k-1}^{\dot{y}} \end{cases}$$

- in this case

$$\mathbf{x}_k = ? \quad \mathbf{F} = ? \quad \mathbf{Q} = ?$$



# Update

$$\boxed{\begin{aligned}\mathbf{x}_k &= \hat{\mathbf{x}}_k + \mathbf{K}_k (\mathbf{z}_k - \hat{\mathbf{z}}_k) \\ \mathbf{P}_k &= \hat{\mathbf{P}}_k - \mathbf{K}_k \mathbf{S}_k \mathbf{K}_k^T\end{aligned}}$$

$$\hat{\mathbf{z}}_k = \mathbf{H} \hat{\mathbf{x}}_k \quad \text{and} \quad \mathbf{S}_k = \mathbf{H} \hat{\mathbf{P}}_k \mathbf{H}^T + \mathbf{R} \quad \text{and} \quad \mathbf{K}_k = \hat{\mathbf{P}}_k \mathbf{H}^T \mathbf{S}_k^{-1}$$

- $\mathbf{x}$  = (updated) state vector
- $\mathbf{z}$  = observation vector ( $\hat{\mathbf{z}}$  is the predicted one)
- $\mathbf{H}$  = matrix of the observation model
- $\mathbf{R}$  = matrix of the observation noise
- $\mathbf{S}$  = innovation matrix
- $\mathbf{K}$  = Kalman gain
- $\mathbf{P}$  = covariance matrix of  $\mathbf{x}$

# KF Update

- Example: Cartesian observations

$$\begin{cases} u_k &= s \cdot x_k + n_k^u \\ v_k &= s \cdot y_k + n_k^v \end{cases}$$

- where

$$\mathbf{x}_k = \begin{bmatrix} x_k \\ y_k \end{bmatrix} \quad \mathbf{z}_k = \begin{bmatrix} u_k \\ v_k \end{bmatrix} \quad \mathbf{H} = \begin{bmatrix} s & 0 \\ 0 & s \end{bmatrix}$$

$$\mathbf{R} = \begin{bmatrix} \sigma_{nu}^2 & 0 \\ 0 & \sigma_{nv}^2 \end{bmatrix}$$

- and  $\mathbf{S}$ ,  $\mathbf{K}$ ,  $\mathbf{P}$  are computed as specified

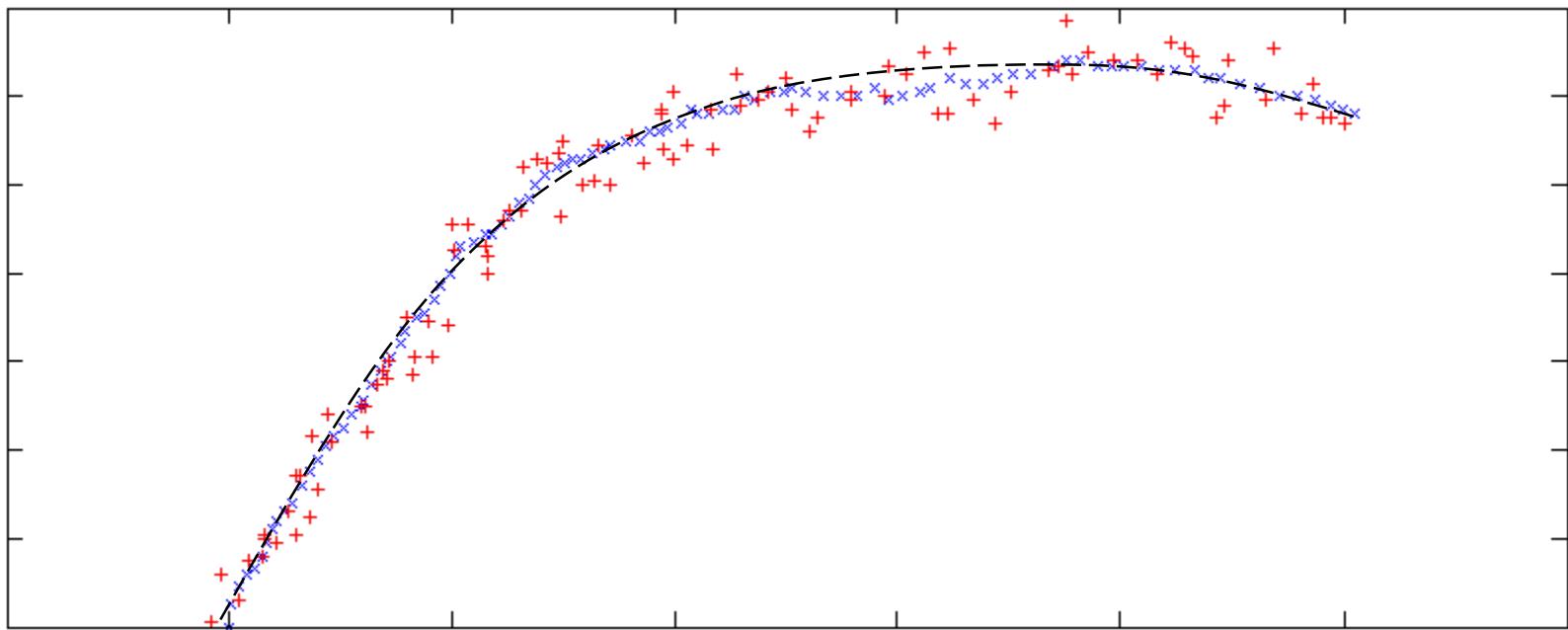
# KF Initialization and Iteration

- Initial values of the state vector  $\mathbf{x}_0$  and covariance matrix  $\mathbf{P}_0$  must be known (e.g.  $\mathbf{x}_0 = [0 \ 0]^T$  and  $\mathbf{P}_0 = \mathbf{Q}$ )
- 1) Prediction: compute (predicted)  $\mathbf{x}_1$  and  $\mathbf{P}_1$
  - 2) Update:
    - compute innovation  $\mathbf{S}$  and gain  $\mathbf{K}$
    - update  $\mathbf{x}_1$  and  $\mathbf{P}_1$  using current  $\mathbf{z}_1$
- Repeat from point 1)

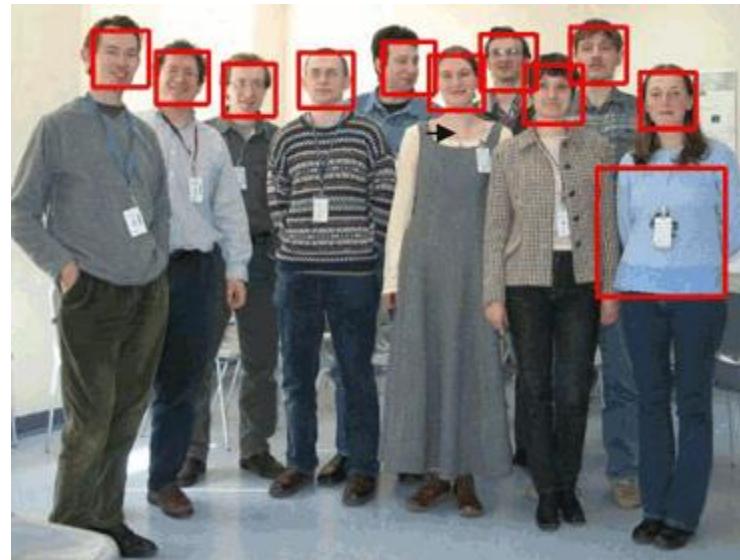


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# E.g.: Trajectory Tracking



# Multi-target Tracking



<https://www.youtube.com/watch?v=3gJZr-DPzcl>



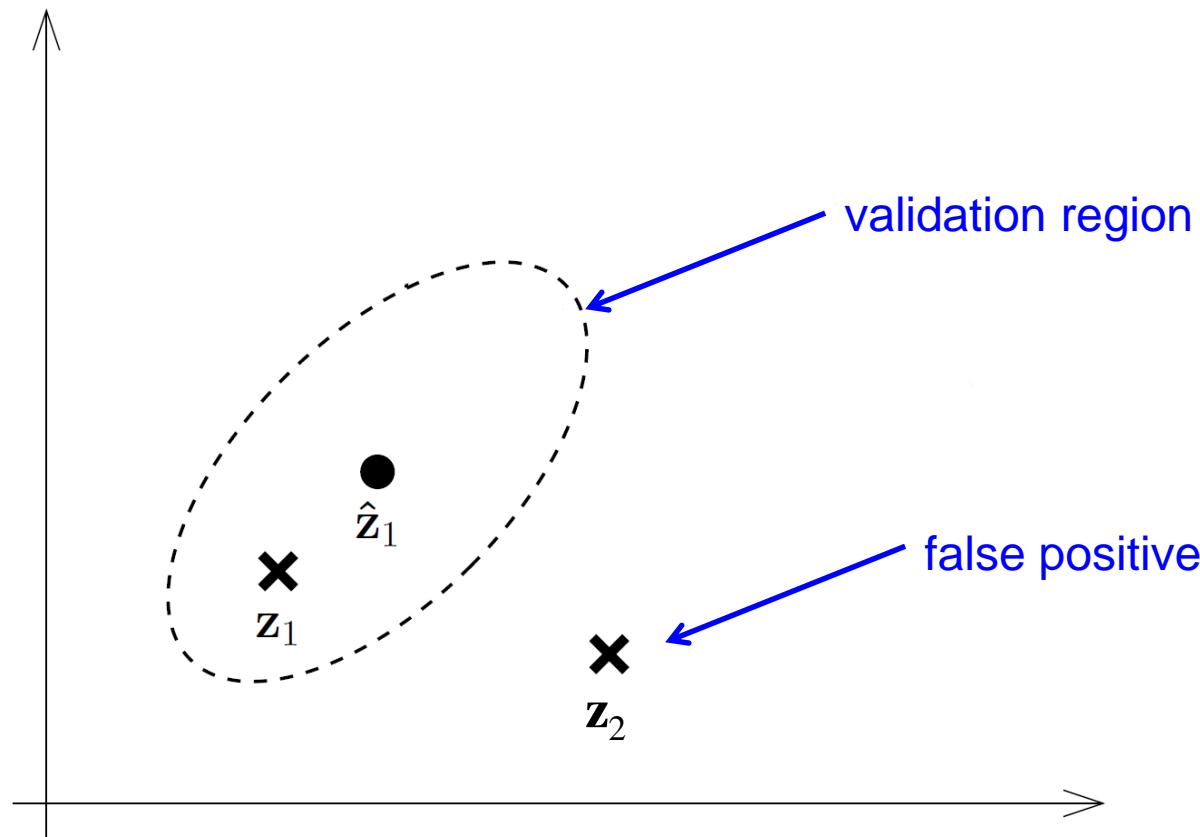
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# Gating and Data Association

- What happen if there are observations which are completely wrong (i.e. false positives), maybe generated by a different target?
- Before updating the KF, it might be necessary to perform the following:
  - **Validation gating** – get rid of observations that could not have been generated by the target
  - **Data association** – if more than one target, associate the right observation to the right target

# Example: Validation Gating

- The dot is the predicted observation, the cross is the real one from the sensor



# Validation Gating

- A simple way to determine the validation region is to consider the maximum distance that the target could have travelled, since the previous time step, if moving at maximum speed
- A better solution is to compute the (squared) **Mahalanobis distance** for observation  $i$  and target  $j$ , and check if it is less than a threshold:

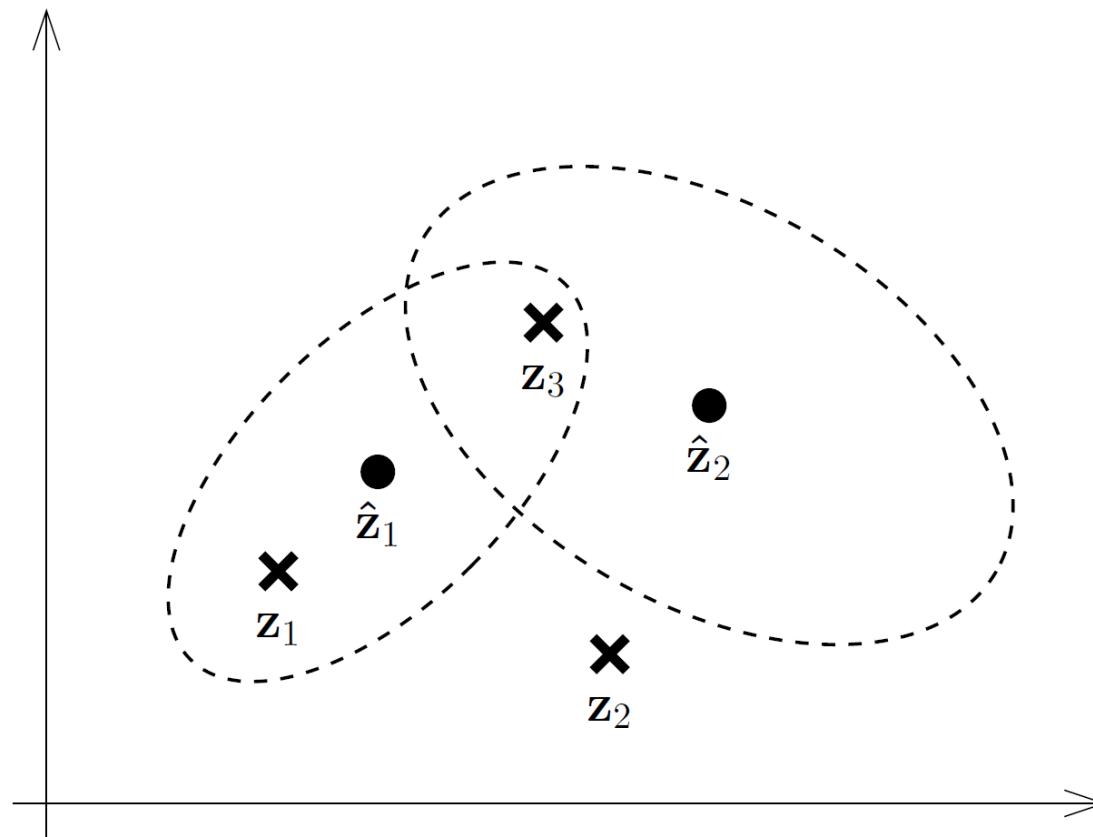
$$(\mathbf{z}_i - \hat{\mathbf{z}}_j)^T \mathbf{S}_{ij}^{-1} (\mathbf{z}_i - \hat{\mathbf{z}}_j) \leq \lambda$$

( $\lambda = 9.21$  for 2D observations)

- If the inequality does not hold, then the observation is considered a false positive and not used to update the KF

# Example: Data Association

- The dots are the predicted observations for 2 separate targets (i.e. 2 separate KFs)





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# NN Data Association

- **Nearest Neighbour (NN)** data association is one of the simplest methods to associate multiple observations to multiple targets
- The squared Mahalanobis distance  $(\mathbf{z}_i - \hat{\mathbf{z}}_j)^T \mathbf{S}_{ij}^{-1} (\mathbf{z}_i - \hat{\mathbf{z}}_j)$  is computed for all the possible combinations of observation  $i$  and target  $j$
- The combination  $(i, j)$  for which the Mahalanobis distance is minimum will be the chosen association (i.e. filter  $i$  will be updated using observation  $j$ )



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# Conclusions

- Suggested reading
  - Online material
- Next lecture
  - Please check email and BB for updates
- Any question?
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