Computer Vision II – Lecture 9

Beyond Kalman Filters

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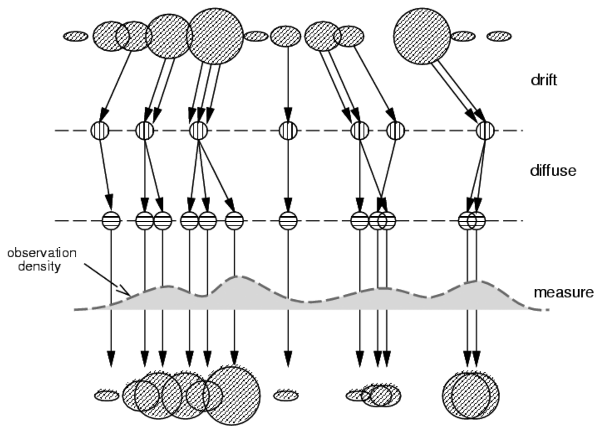
Course Outline

- Single-Object Tracking
  - Background modeling
  - Template based tracking
  - Color based tracking
  - Contour based tracking
  - Tracking by online classification
  - Tracking-by-detection
- Bayesian Filtering
  - Kalman filters
  - Particle filters
  - Case studies
- Multi-Object Tracking
- Articulated Tracking



Today: Beyond Gaussian Error Models

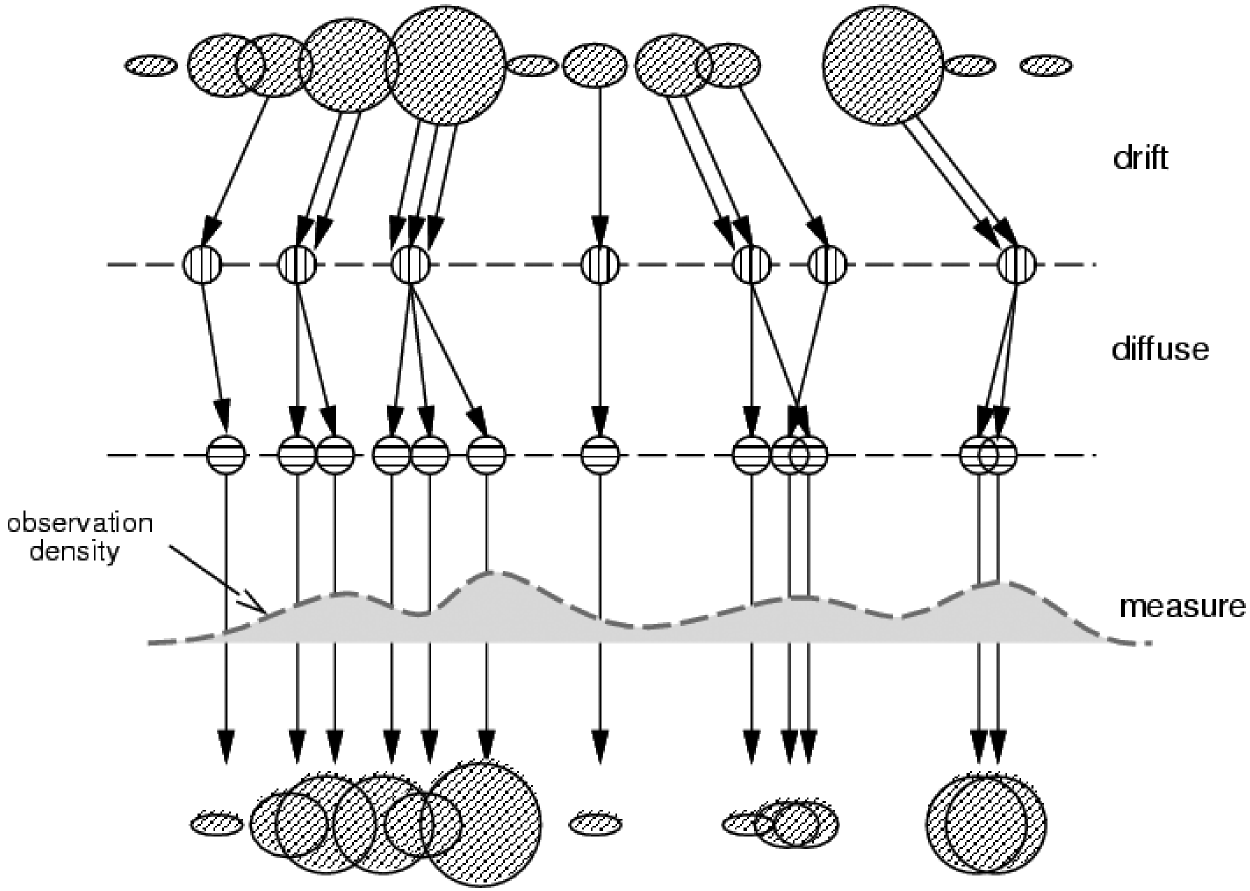


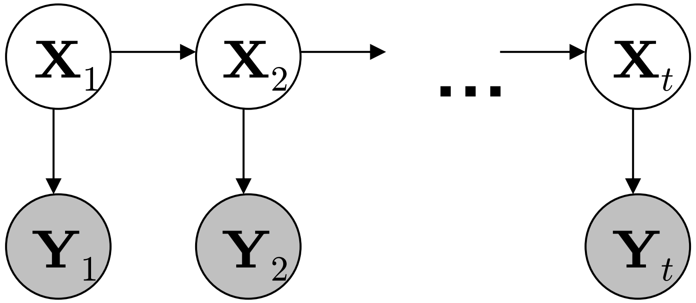
Figure from Isard & Blake

Topics of This Lecture

- Recap: Kalman Filter
  - Basic ideas
  - Limitations
  - Extensions
- Particle Filters
  - Basic ideas
  - Propagation of general densities
  - Factored sampling
- Case study
  - Detector Confidence Particle Filter
  - Role of the different elements

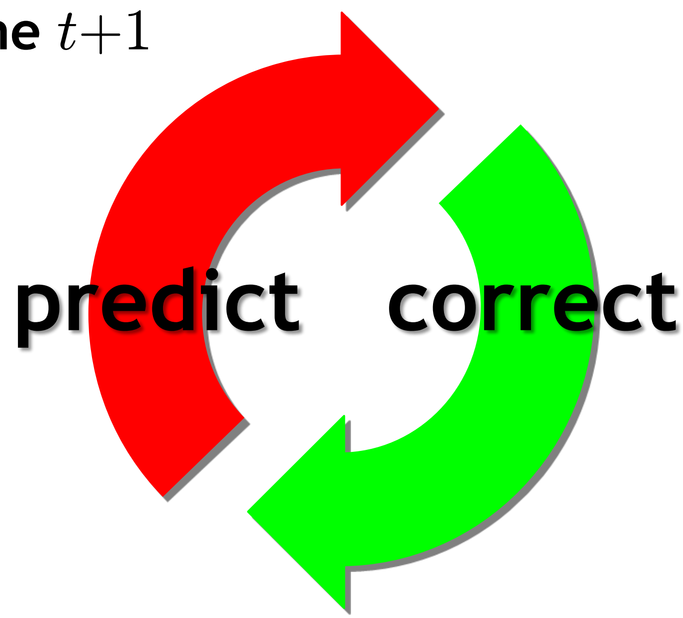
Recap: Tracking as Inference

- Inference problem
  - The hidden state consists of the true parameters we care about, denoted $\mathbf{X}$.
  - The measurement is our noisy observation that results from the underlying state, denoted $\mathbf{Y}$.
  - At each time step, state changes (from $\mathbf{X}_{t-1}$ to $\mathbf{X}_t$) and we get a new observation $\mathbf{Y}_t$.
- Our goal: recover most likely state $\mathbf{X}_t$ given
  - All observations seen so far.
  - Knowledge about dynamics of state transitions.



Recap: Tracking as Induction

- Base case:
  - Assume we have initial prior that predicts state in absence of any evidence: $P(\mathbf{X}_0)$
  - At the first frame, *correct* this given the value of $\mathbf{Y}_0 = \mathbf{y}_0$
- Given corrected estimate for frame t:
  - Predict for frame $t+1$
  - Correct for frame $t+1$



Recap: Prediction and Correction

- **Prediction:**

$$P(X_t \mid y_0,\dots,y_{t-1}) = \int \underbrace{P(X_t \mid X_{t-1})}_{\text{Dynamics model}} \underbrace{P(X_{t-1} \mid y_0,\dots,y_{t-1})}_{\text{Corrected estimate from previous step}} dX_{t-1}$$

- **Correction:**

$$P(X_t \mid y_0,\dots,y_t) = \frac{\overbrace{P(y_t \mid X_t)}^{\text{Observation model}} \overbrace{P(X_t \mid y_0,\dots,y_{t-1})}^{\text{Predicted estimate}}}{\int P(y_t \mid X_t) P(X_t \mid y_0,\dots,y_{t-1}) dX_t}$$

Recap: Linear Dynamic Models

- Dynamics model
  - State undergoes linear tranformation D_t plus Gaussian noise

$$\boldsymbol{x}_t \sim N\left(\boldsymbol{D}_t \boldsymbol{x}_{t-1}, \Sigma_{d_t}\right)$$

- Observation model
  - Measurement is linearly transformed state plus Gaussian noise

$$\boldsymbol{y}_t \sim N\left(\boldsymbol{M}_t \boldsymbol{x}_t, \Sigma_{m_t}\right)$$

Recap: Constant Velocity Model (1D)

- **State vector: position p and velocity v**

$$x_t = \begin{bmatrix} p_t \\ v_t \end{bmatrix} \qquad \begin{aligned} p_t &= p_{t-1} + (\Delta t) v_{t-1} + \varepsilon \\ v_t &= v_{t-1} + \xi \end{aligned}$$

(greek letters denote noise terms)

$$x_t = D_t x_{t-1} + noise = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix} \begin{bmatrix} p_{t-1} \\ v_{t-1} \end{bmatrix} + noise$$

- **Measurement is position only**

$$y_t = M x_t + noise = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} p_t \\ v_t \end{bmatrix} + noise$$

Recap: Constant Acceleration Model (1D)

- **State vector: position p, velocity v, and acceleration a.**

$$x_t = \begin{bmatrix} p_t \\ v_t \\ a_t \end{bmatrix} \qquad \begin{aligned} p_t &= p_{t-1} + (\Delta t) v_{t-1} + \varepsilon \\ v_t &= v_{t-1} + (\Delta t) a_{t-1} + \xi \\ a_t &= a_{t-1} + \zeta \end{aligned}$$

(greek letters denote noise terms)

$$x_t = D_t x_{t-1} + noise = \begin{bmatrix} 1 & \Delta t & 0 \\ 0 & 1 & \Delta t \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} p_{t-1} \\ v_{t-1} \\ a_{t-1} \end{bmatrix} + noise$$

- **Measurement is position only**

$$y_t = M x_t + noise = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} p_t \\ v_t \\ a_t \end{bmatrix} + noise$$

Recap: General Motion Models

- Assuming we have differential equations for the motion
  - E.g. for (undampened) periodic motion of a pendulum

$$\frac{d^2 p}{dt^2} = -p$$

- Substitute variables to transform this into linear system

$$p_1 = p \qquad p_2 = \frac{dp}{dt} \qquad p_3 = \frac{d^2 p}{dt^2}$$

- Then we have

$$x_t = \begin{bmatrix} p_{1,t} \\ p_{2,t} \\ p_{3,t} \end{bmatrix} \qquad \begin{aligned} p_{1,t} &= p_{1,t-1} + (\Delta t) p_{2,t-1} + \varepsilon \\ p_{2,t} &= p_{2,t-1} + (\Delta t) p_{3,t-1} + \xi \\ p_{3,t} &= -p_{1,t-1} + \zeta \end{aligned} \qquad D_t = \begin{bmatrix} 1 & \Delta t & 0 \\ 0 & 1 & \Delta t \\ -1 & 0 & 0 \end{bmatrix}$$

Recap: The Kalman Filter

Know corrected state from previous time step, and all measurements up to the current one
→ Predict distribution over next state.

Receive measurement

Know prediction of state, and next measurement
→Update distribution over current state.

Time update ("Predict")

Measurement update ("Correct")

$$P\left(X_t \middle| y_0, \ldots, y_{t-1}\right)$$

Time advances: t++

$$P\left(X_t \middle| y_0, \ldots, y_t\right)$$

Mean and std. dev. of predicted state:

$$\mu_t^-, \sigma_t^-$$

Mean and std. dev. of corrected state:

$$\mu_t^+, \sigma_t^+$$

Recap: General Kalman Filter (>1dim)

- What if state vectors have more than one dimension?

PREDICT

$$x_t^- = D_t x_{t-1}^+$$

$$\Sigma_t^- = D_t \Sigma_{t-1}^+ D_t^T + \Sigma_{d_t}$$

CORRECT

$$K_t = \Sigma_t^- M_t^T \left(M_t \Sigma_t^- M_t^T + \Sigma_{m_t} \right)^{-1}$$

"Kalman gain" "residual"

$$x_t^+ = x_t^- + K_t \left(y_t - M_t x_t^- \right)$$

$$\Sigma_t^+ = \left(I - K_t M_t \right) \Sigma_t^-$$

More weight on residual when measurement error covariance approaches 0.

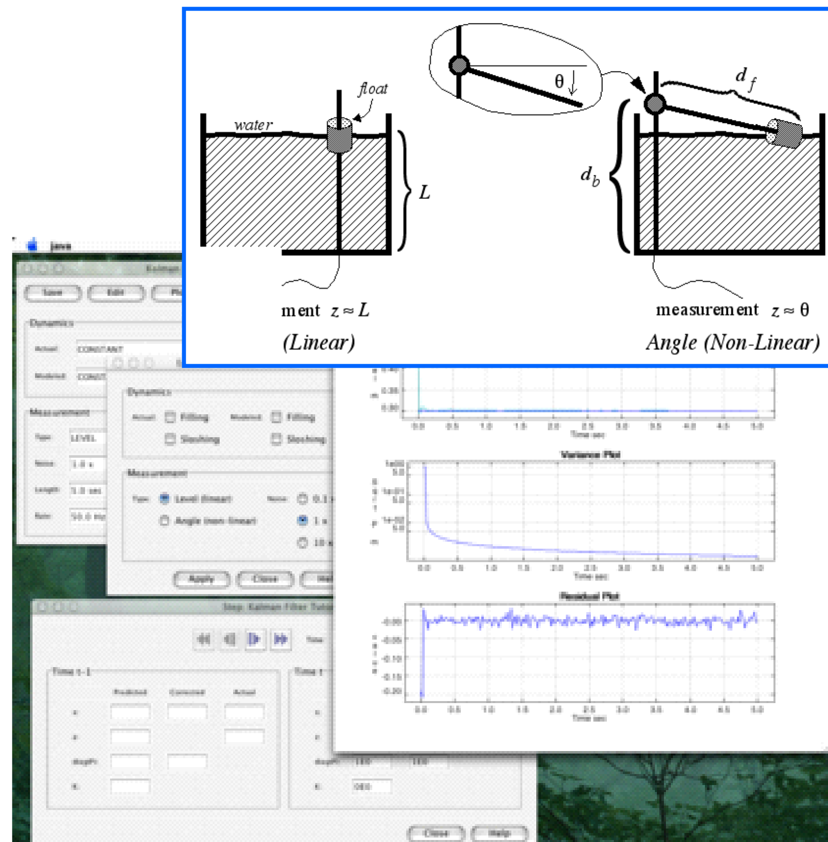
Less weight on residual as a priori estimate error covariance approaches 0.

for derivations, see F&P Chapter 17.3

Resources: Kalman Filter Web Site

http://www.cs.unc.edu/~welch/kalman

- Electronic and printed references
  - Book lists and recommendations
  - Research papers
  - Links to other sites
  - Some software
- News
- Java-Based KF Learning Tool
  - On-line 1D simulation
  - Linear and non-linear
  - Variable dynamics



Remarks

- Try it!
  - Not too hard to understand or program
- Start simple
  - Experiment in 1D
  - Make your own filter in Matlab, etc.
- Note: the Kalman filter "wants to work"
  - Debugging can be difficult
  - Errors can go un-noticed

Slide adapted from Greg Welch

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  - Limitations
  - Extensions
- Particle Filters
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Extension: Extended Kalman Filter (EKF)

- Basic idea
  - State transition and observation model don't need to be linear functions of the state, but just need to be differentiable.

$$x_t = f\left(x_{t-1}, u_t\right) + \varepsilon$$

$$y_t = h\left(x_t\right) + \xi$$

  - The EKF essentially linearizes the nonlinearity around the current estimate by a Taylor expansion.

- Properties
  - Unlike the linear KF, the EKF is in general *not* an optimal estimator.
    - If the initial estimate is wrong, the filter may quickly diverge.
  - Still, it's the de-facto standard in many applications
    - Including navigation systems and GPS

Kalman Filter - Other Extensions

- Unscented Kalman Filter (UKF)
  - Further development of EKF
  - Probability density is approximated by nonlinear transform of a random variable.
  - More accurate results than the EKF's Taylor expansion approx.
- Ensemble Kalman Filter (EnKF)
  - Represents the distribution of the system state using a collection (an *ensemble*) of state vectors.
  - Replace covariance matrix by *sample covariance* from ensemble.
  - Still basic assumption that all prob. distributions involved are Gaussian.
  - EnKFs are especially suitable for problems with a large number of variables.

Even More Extensions

Switching linear dynamical system (SLDS):

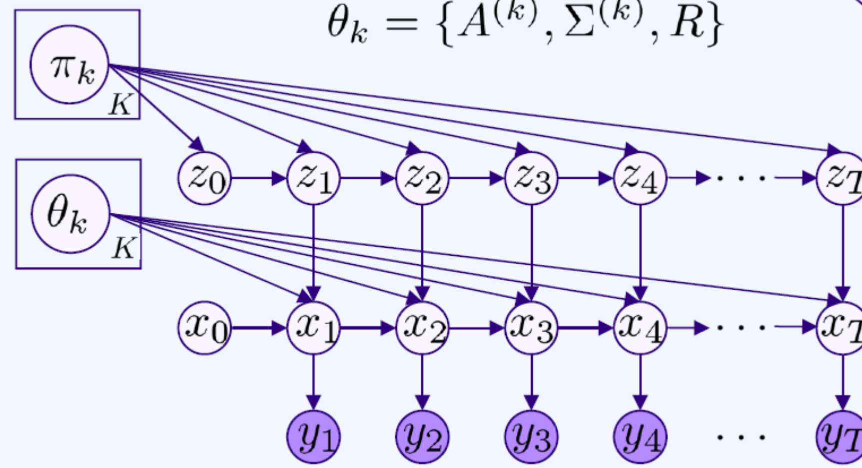
$$z_t \sim \pi_{z_{t-1}}$$

$$x_t = A^{(z_t)} x_{t-1} + e_t(z_t)$$

$$y_t = C x_t + w_t$$

$$e_t \sim \mathcal{N}(0, \Sigma^{(z_t)}) \quad w_t \sim \mathcal{N}(0, R)$$

$$\theta_k = \{A^{(k)}, \Sigma^{(k)}, R\}$$



- **Switching Linear Dynamic System (SLDS)**
  - **Use a set of k dynamic models $A^{(1)},\ldots,A^{(k)}$, each of which describes a different dynamic behavior.**
  - **Hidden variable z_t determines which model is active at time t.**
  - **A switching process can change z_t according to distribution $\pi_{z_{t-1}}$.**

Figure source: Erik Sudderth

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Today: only main ideas

Formal introduction next Tuesday

When Is A Single Hypothesis Too Limiting?

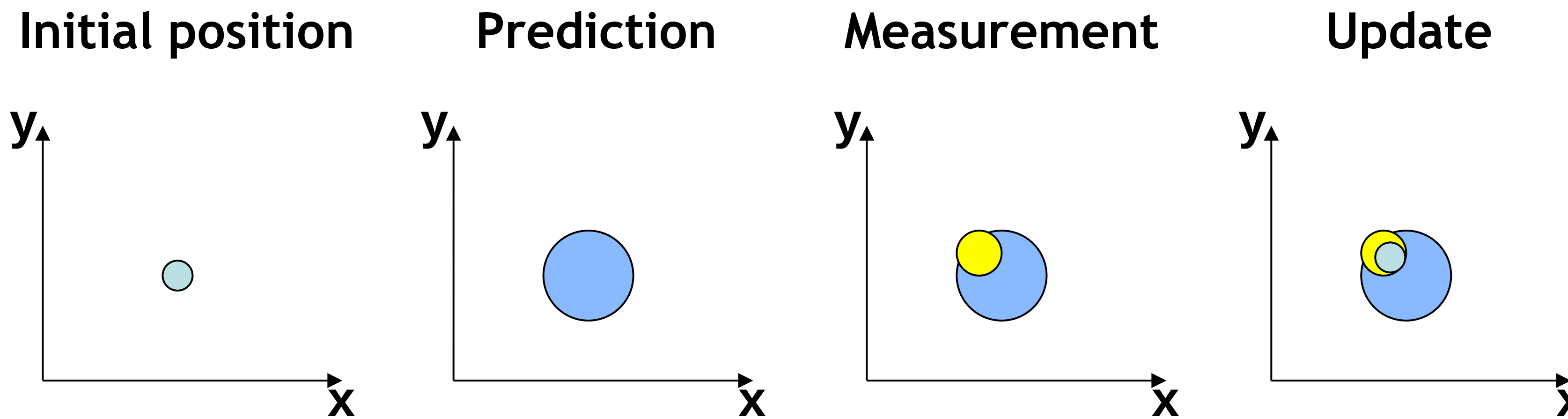
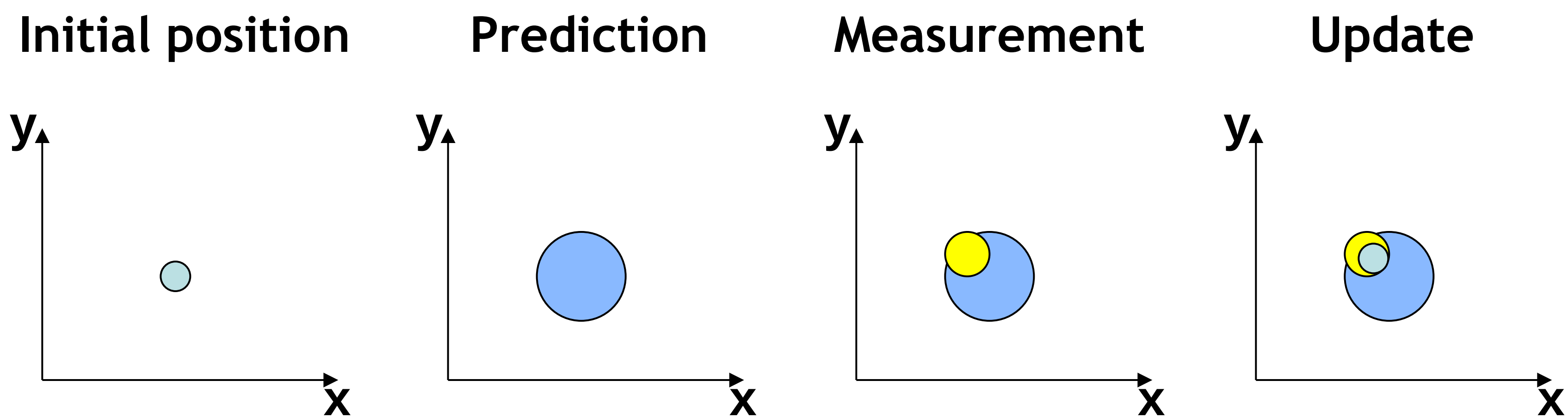


Figure from Thrun & Kosecka

When Is A Single Hypothesis Too Limiting?



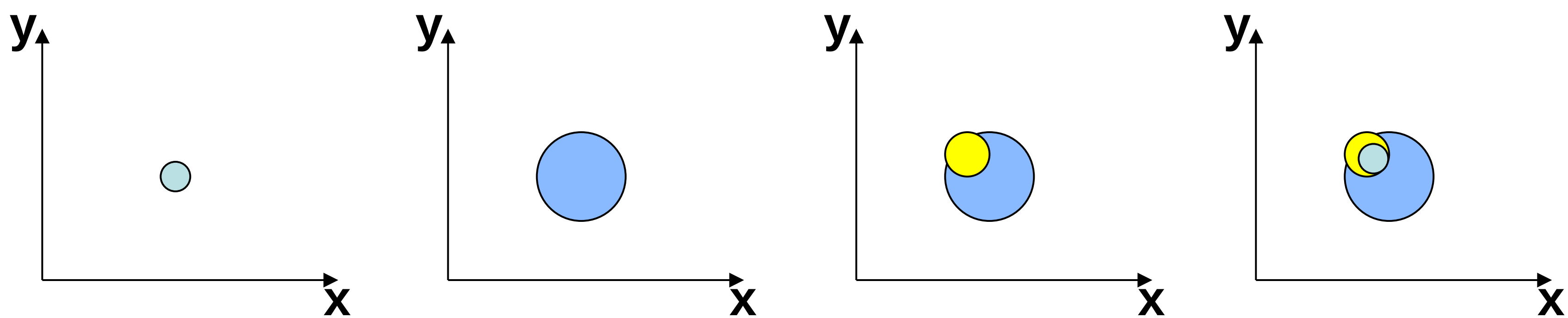
- **Consider this example: say we are tracking the face on the right using a skin color blob to get our measurement.**

Video from Jojic & Frey

Figure from Thrun & Kosecka

When Is A Single Hypothesis Too Limiting?

Initial position | Prediction | Measurement | Update



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Video from Jojic & Frey

Propagation of General Densities

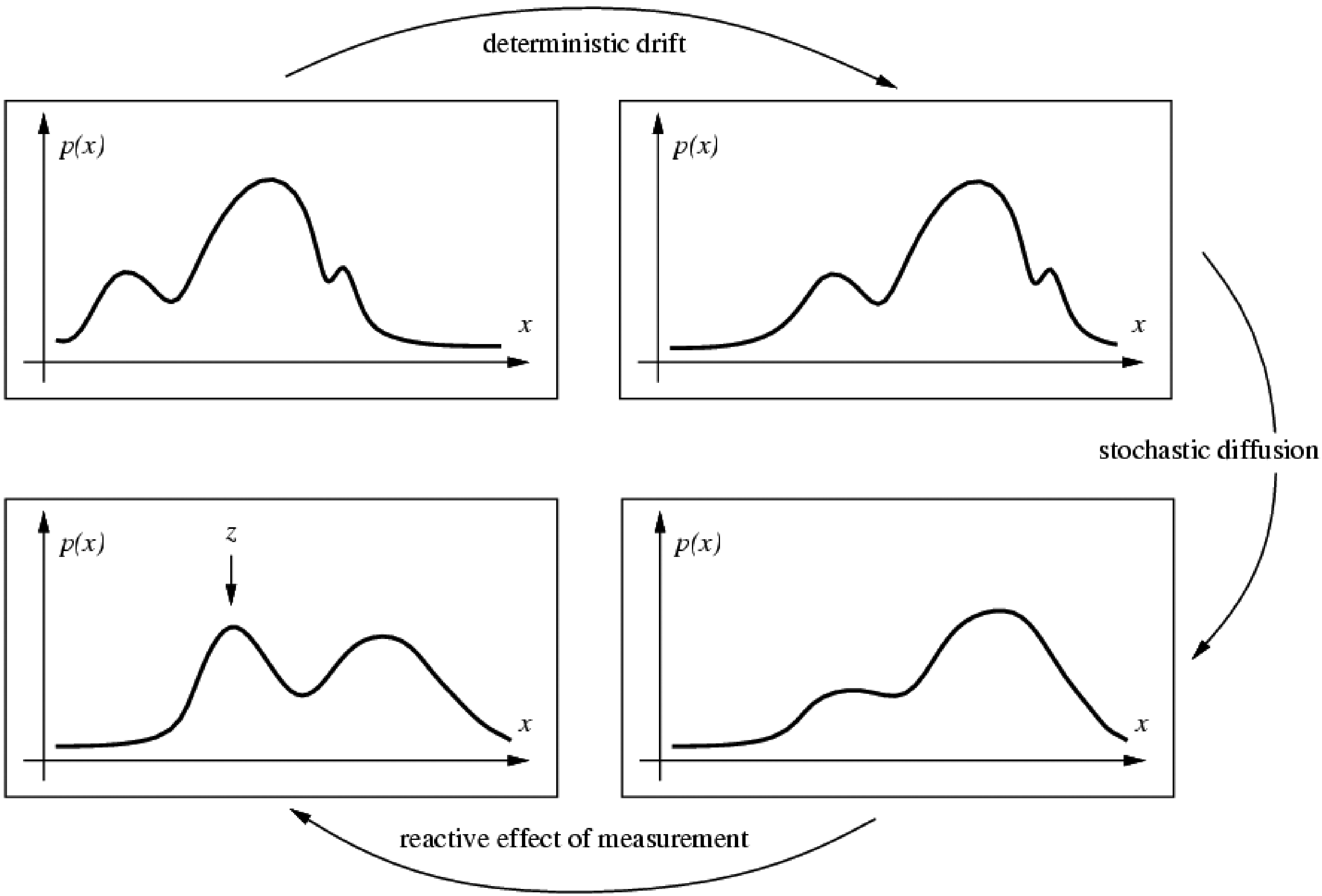
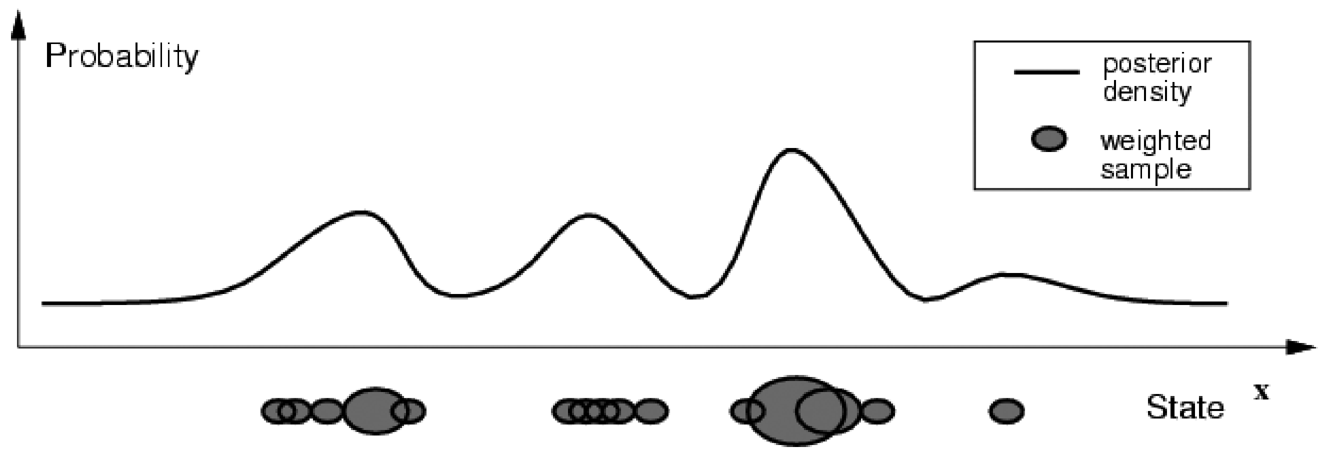


Figure from Isard & Blake

Factored Sampling



- **Idea: Represent state distribution non-parametrically**
  - **Prediction: Sample points from prior density for the state,** $P(X)$
  - **Correction: Weight the samples according to** $P(Y|X)$

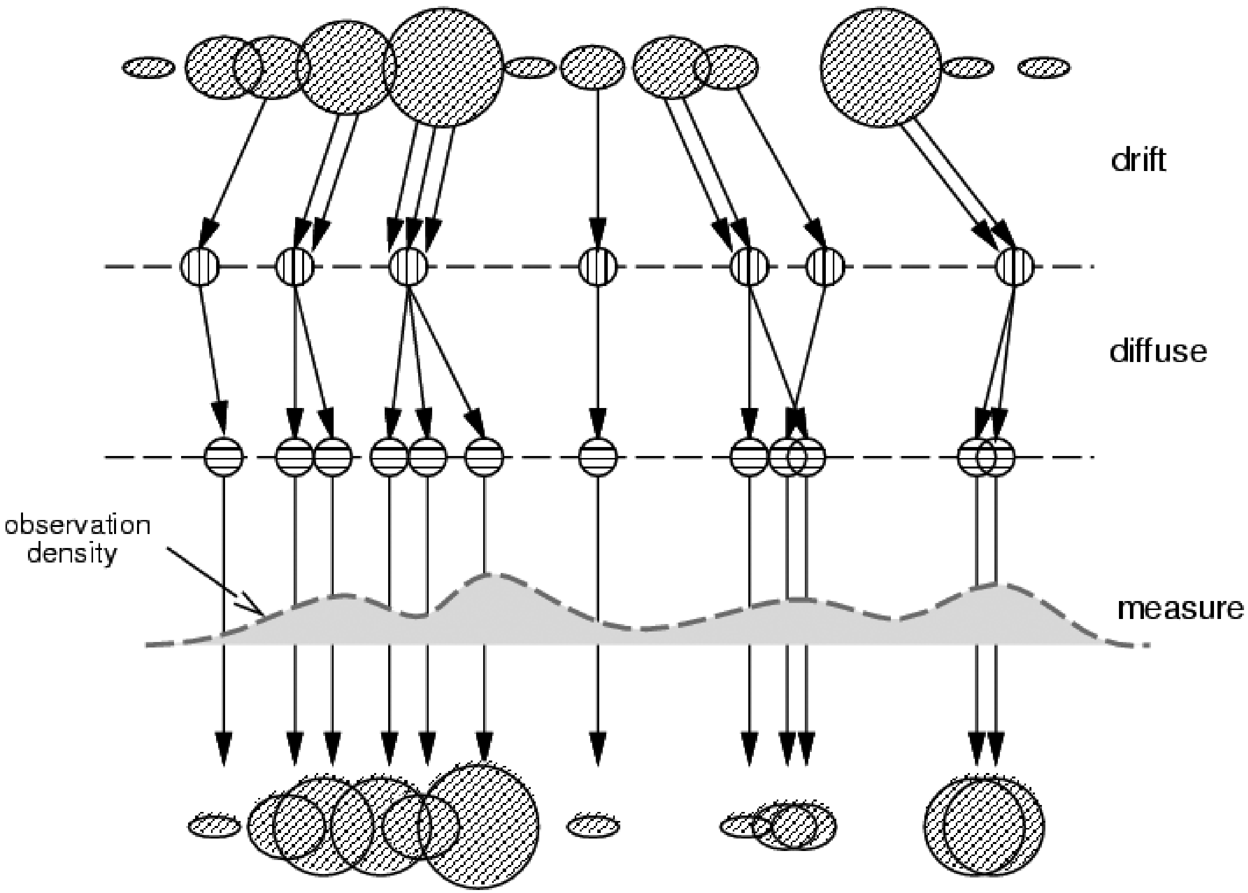
$$P(X_t \mid y_0, \ldots, y_t) = \frac{P(y_t \mid X_t)P(X_t \mid y_0, \ldots, y_{t-1})}{\int P(y_t \mid X_t)P(X_t \mid y_0, \ldots, y_{t-1})dX_t}$$

Particle Filtering

- (Also known as Sequential Monte Carlo Methods)

- Idea
  - We want to use sampling to propagate densities over time (i.e., across frames in a video sequence).
  - At each time step, represent posterior $P(X_t \mid Y_t)$ with weighted sample set.
  - Previous time step's sample set $P(X_{t-1} \mid Y_{t-1})$ is passed to next time step as the effective prior.

Particle Filtering



- Start with weighted samples from previous time step
- Sample and shift according to dynamics model
- Spread due to randomness; this is pre-dicted density $P(X_t | Y_{t-1})$
- Weight the samples according to observation density
- Arrive at corrected density estimate $P(X_t | Y_t)$

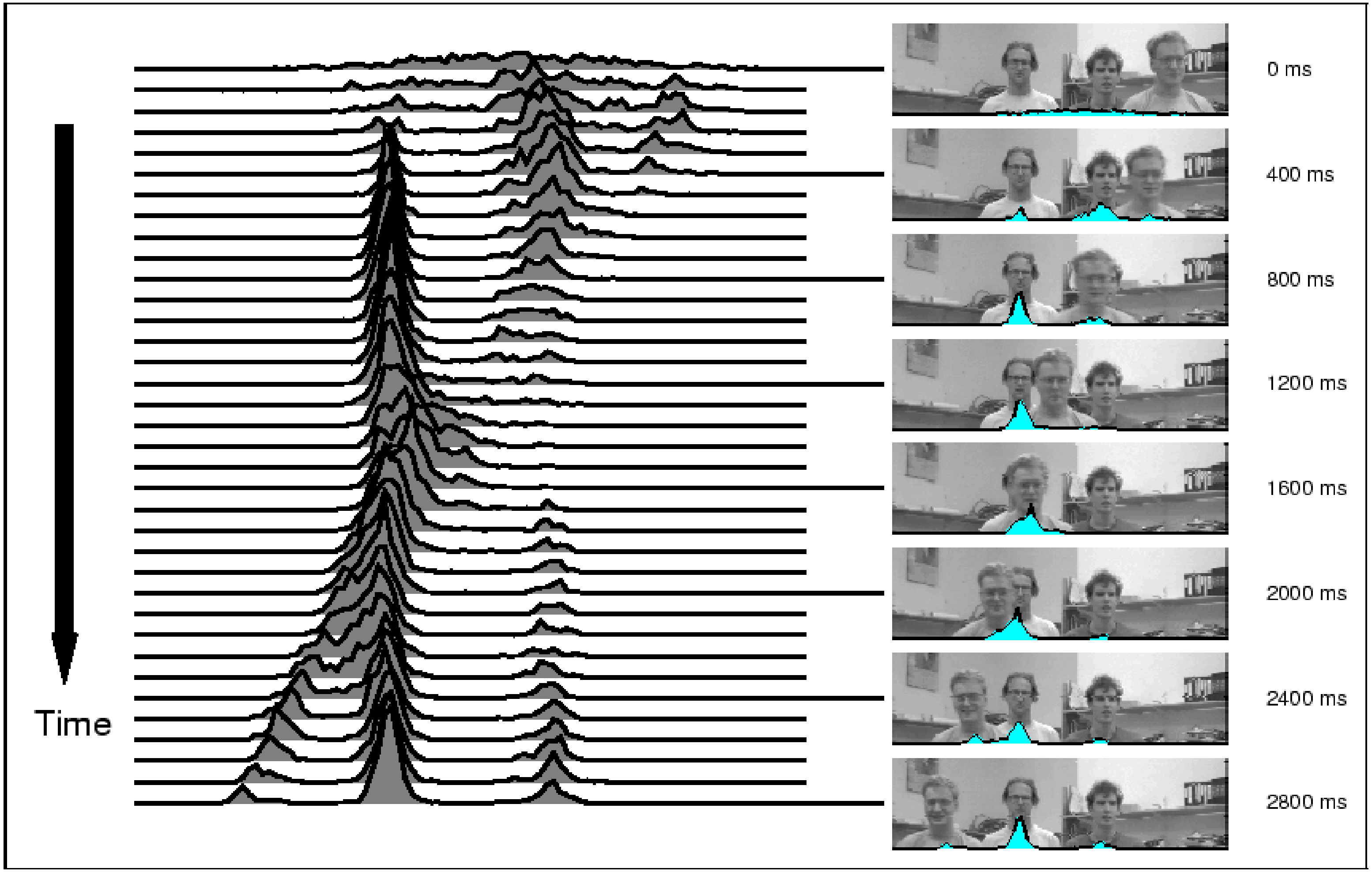
M. Isard and A. Blake, CONDENSATION -- conditional density propagation for visual tracking, IJCV 29(1):5-28, 1998

Particle Filtering – Visualization

Code and video available from

http://www.robots.ox.ac.uk/~misard/condensation.html

Particle Filtering Results



http://www.robots.ox.ac.uk/~misard/condensation.html

Figure from Isard & Blake

Particle Filtering Results

- Some more examples

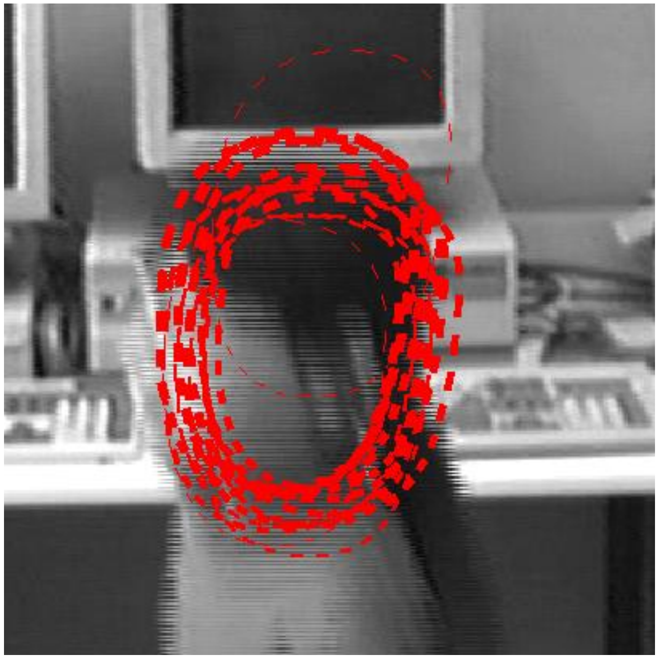
http://www.robots.ox.ac.uk/~misard/condensation.html

Videos from Isard & Blake

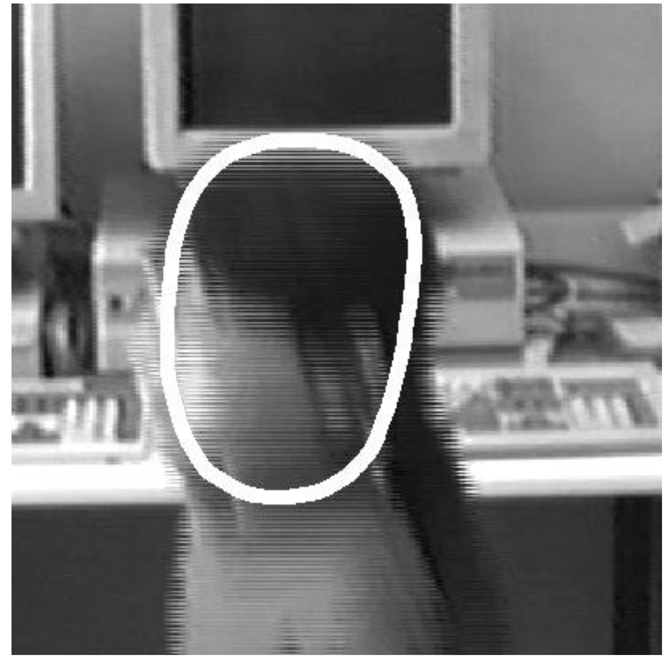
Obtaining a State Estimate

- Note that there's no explicit state estimate maintained, just a "cloud" of particles
- Can obtain an estimate at a particular time by querying the current particle set
- Some approaches
  - "Mean" particle
    - Weighted sum of particles
    - Confidence: inverse variance
  - Really want a mode finder—mean of tallest peak

Condensation: Estimating Target State



State samples
(thickness proportional to weight)



From *Isard & Blake, 1998*

Mean of weighted
state samples

Summary: Particle Filtering

- **Pros:**
  - Able to represent arbitrary densities
  - Converging to true posterior even for non-Gaussian and nonlinear system
  - Efficient: particles tend to focus on regions with high probability
  - Works with many different state spaces
    - E.g. articulated tracking in complicated joint angle spaces
  - Many extensions available

Summary: Particle Filtering

- **Cons / Caveats:**
  - #Particles is important performance factor
    - Want as few particles as possible for efficiency.
    - But need to cover state space sufficiently well.
  - Worst-case complexity grows exponentially in the dimensions
  - Multimodal densities possible, but still single object
    - Interactions between multiple objects require special treatment.
    - Not handled well in the particle filtering framework (state space explosion).

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- **Case study**
  - **Detector Confidence Particle Filter**
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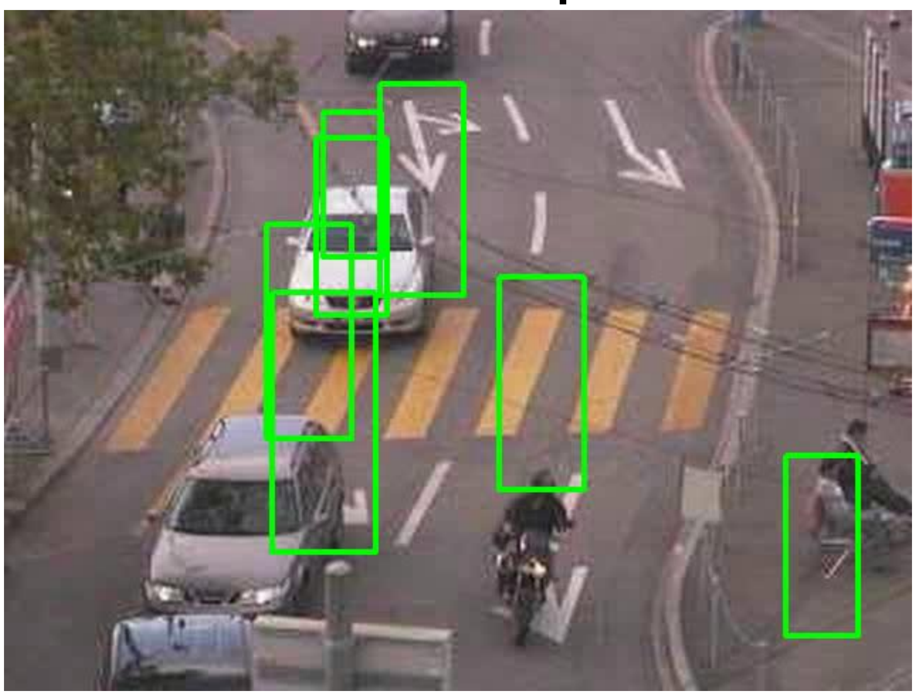
Challenge: Unreliable Object Detectors

- **Example:**
  - Low-res webcam footage (320×240), MPEG compressed

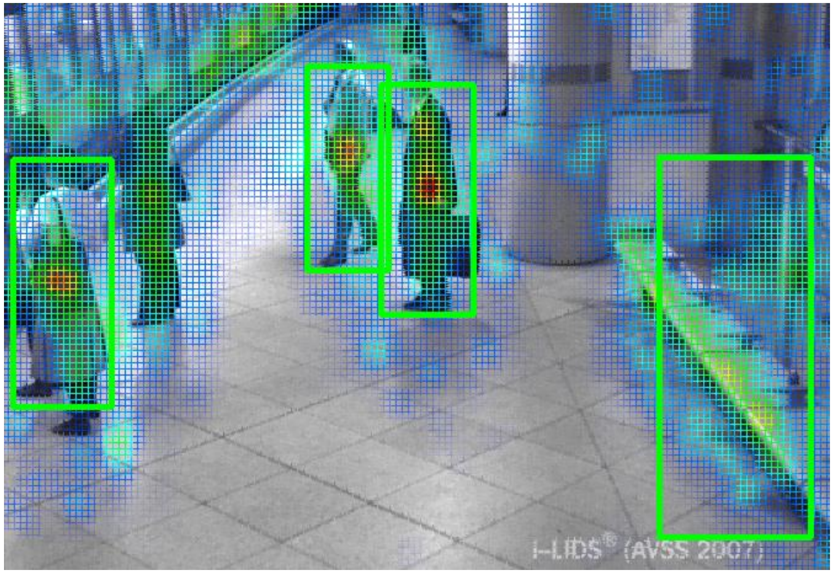
Detector input



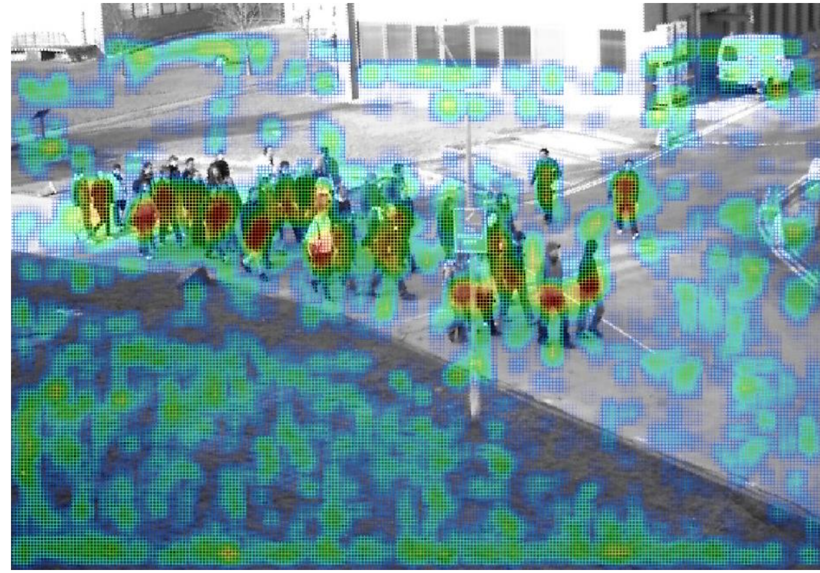
Tracker output

How to get from here... ? ...to here?

Tracking based on Detector Confidence



(using ISM detector)

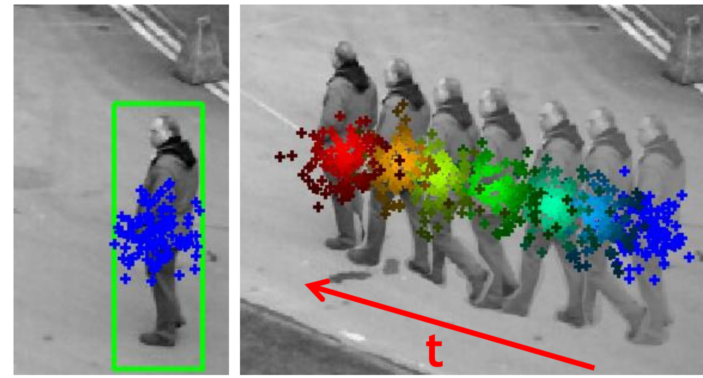


(using HOG detector)

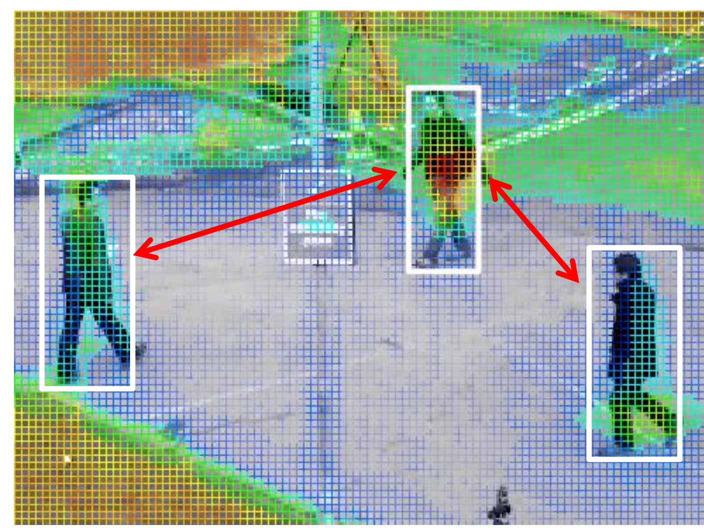
- Detector output is often not perfect
  - Missing detections and false positives
  - But continuous confidence still contains useful cues.
- Idea employed here:
  - Use continuous detector confidence to track persons over time.

Main Ideas

- **Detector confidence particle filter**
  - Initialize particle cloud on strong object detections.
  - Propagate particles using continuous detector confidence as observation model.



- **Disambiguate between different persons**
  - Train a person-specific classifier with online boosting.
  - Use classifier output to distinguish between nearby persons.

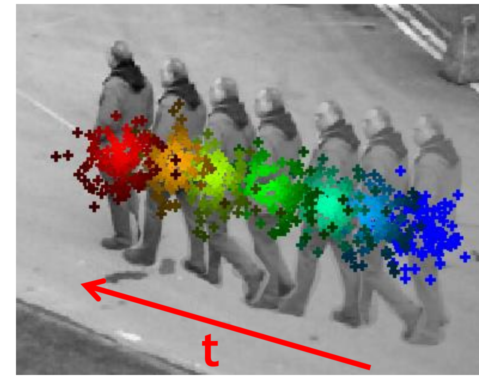


[Breitenstein, Reichlin, Leibe et al., ICCV'09]

Detector Confidence Particle Filter

- **State:** $x = \{x, y, u, v\}$
- **Motion model (constant velocity)**

$$
\begin{aligned}
(x, y)_t &= (x, y)_{t-1} + (u, v)_{t-1} \cdot \Delta t + \varepsilon_{(x,y)} \\
(u, v)_t &= (u, v)_{t-1} + \varepsilon_{(u,v)}
\end{aligned}
$$



- **Observation model**

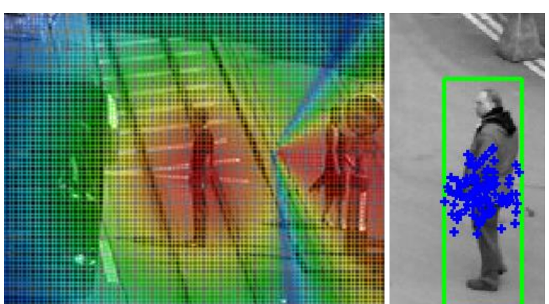
$$w_{tr,p} = p(y_t | x_t^{(i)}) =$$

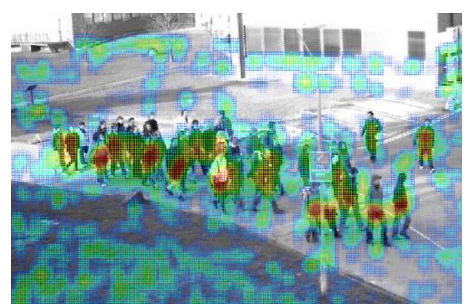
$$\beta \cdot \mathcal{I}(tr) \cdot p_{\mathcal{N}}(p - d^*) + \gamma \cdot d_c(p) \cdot p_o(tr) + \eta \cdot c_{tr}(p)$$

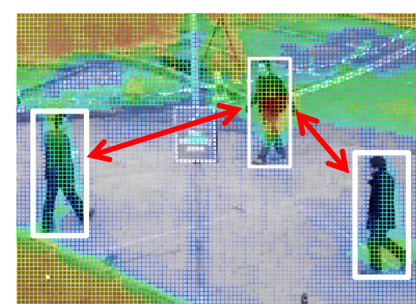
Discrete detections

Detector confidence

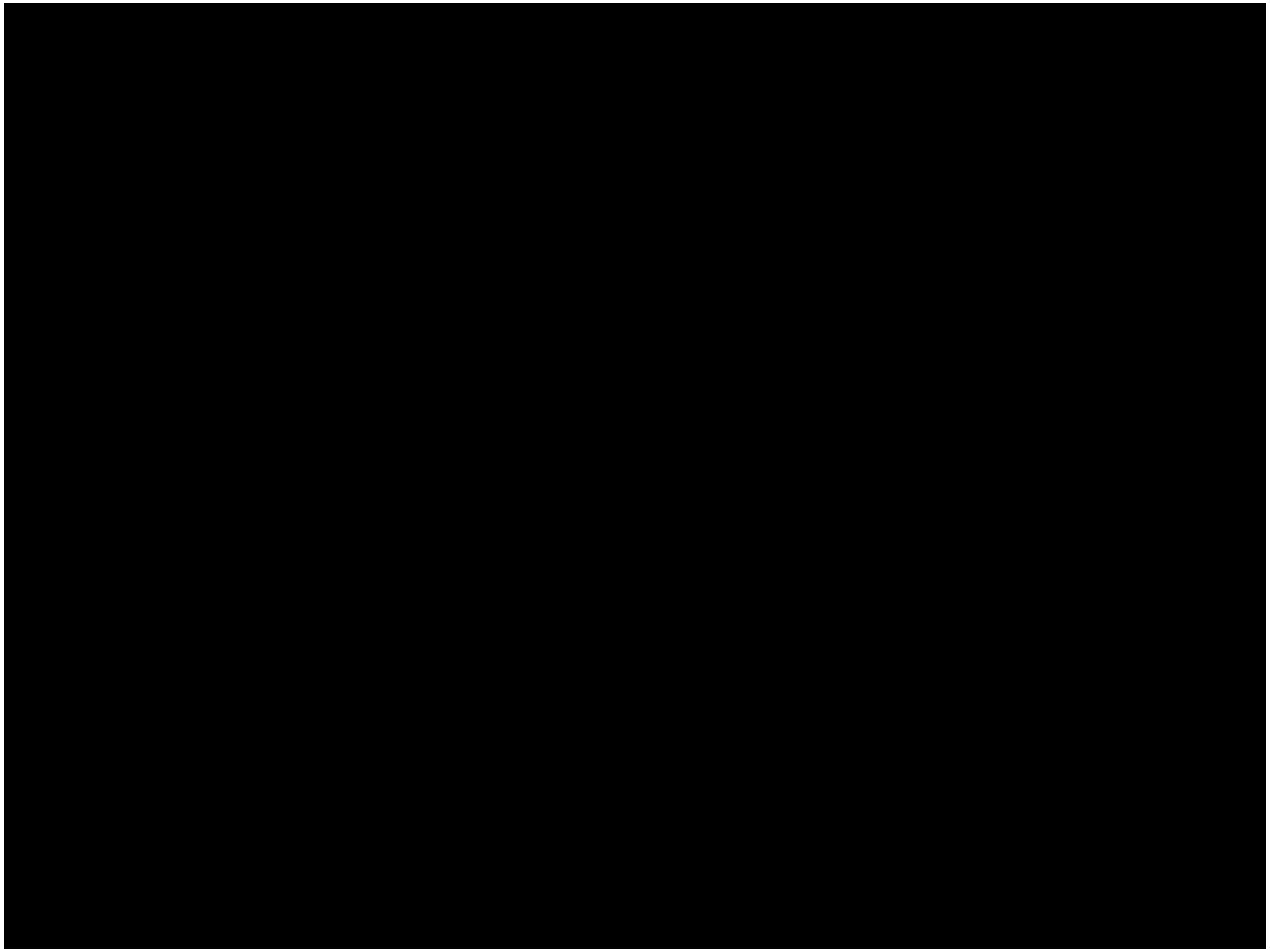
Classifier confidence







When Is Which Term Useful?

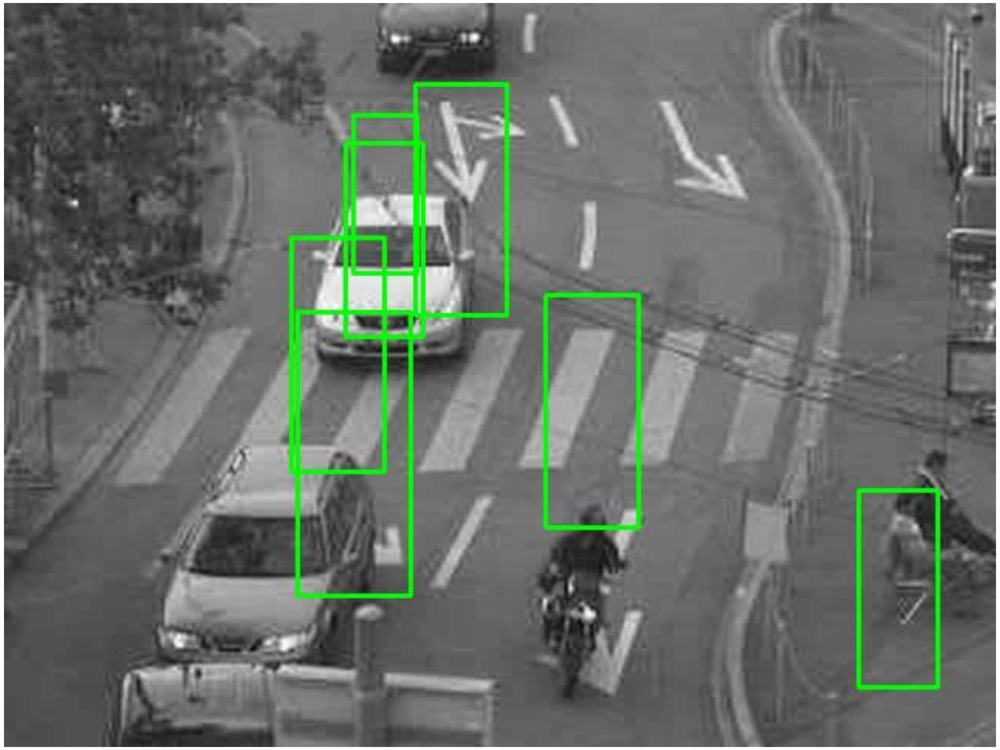


Discrete detections   Detector confidence   Classifier confidence

Each Observation Term Increases Robustness!

Observation Model Terms	MOTP	MOTA	FN	FP	ID Sw.
1: Det+DetConf+Class	70.0%	72.9%	26.8%	0.3%	0
2: Det+DetConf	64.0%	54.5%	28.2%	17.2%	5
3: Det+Class	65.0%	55.3%	31.3%	13.4%	0
4: Det	67.0%	40.9%	30.7%	28.0%	10

Detector only



CLEAR MOT scores

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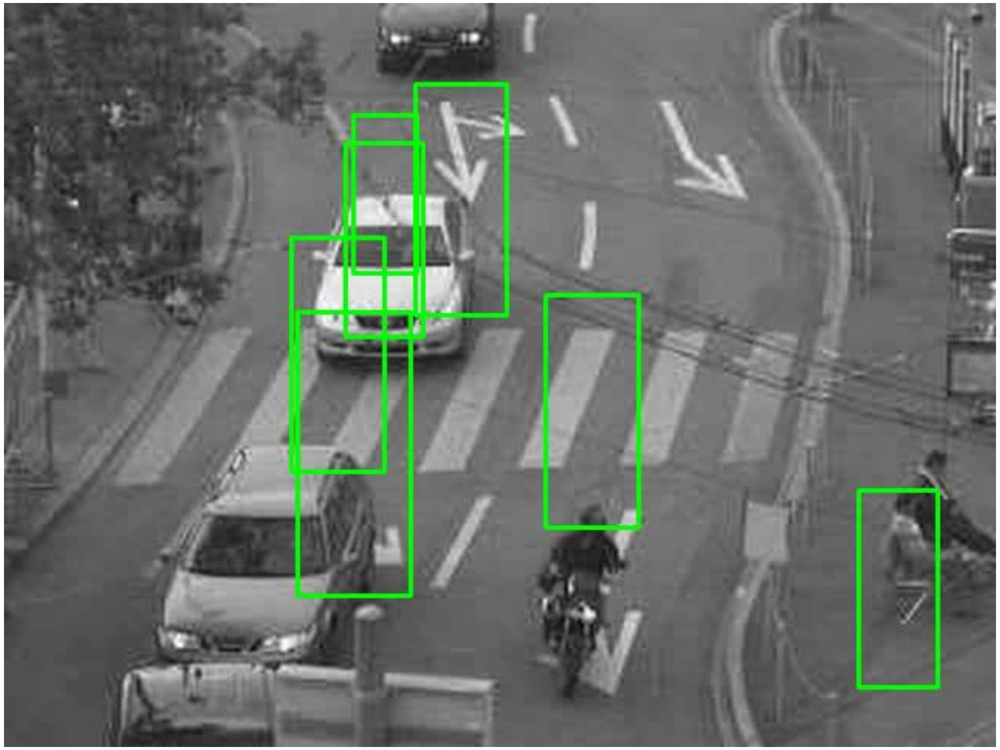
4: Det	67.0%	40.9%	30.7%	28.0%	10

Detector
+ Confidence



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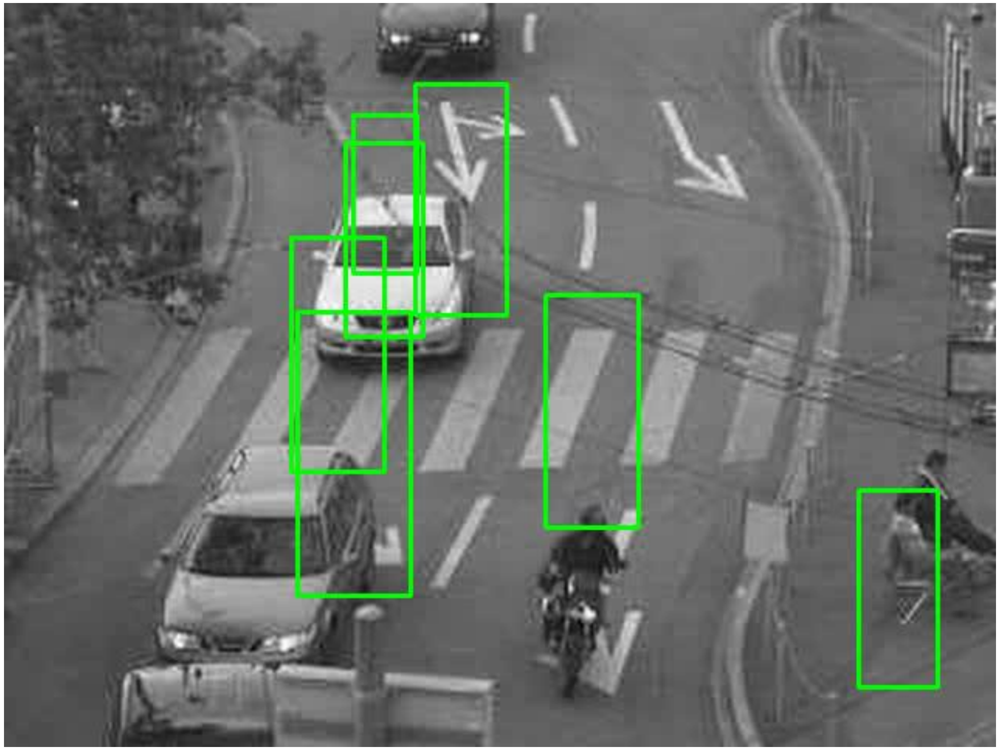
Detector
+ Classifier



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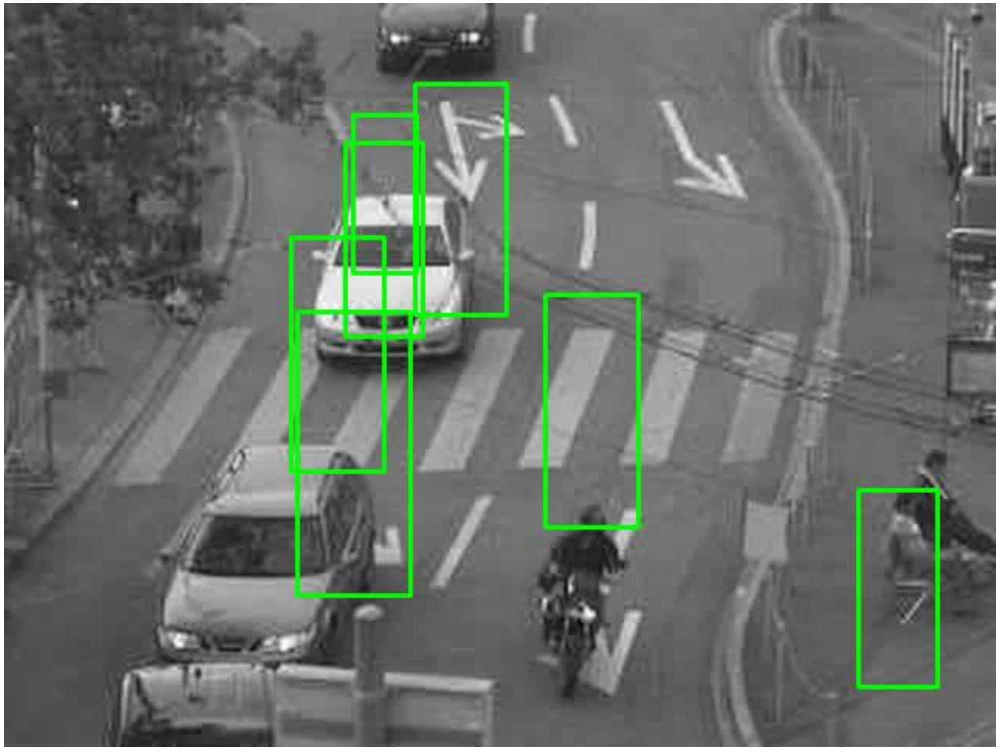
1: Det+DetConf+Class	70.0%	72.9%	26.8%	0.3%	0
2: Det+DetConf	64.0%	54.5%	28.2%	17.2%	5
3: Det+Class	65.0%	55.3%	31.3%	13.4%	0
4: Det	67.0%	40.9%	30.7%	28.0%	10

Detector
+ Confidence
+ Classifier

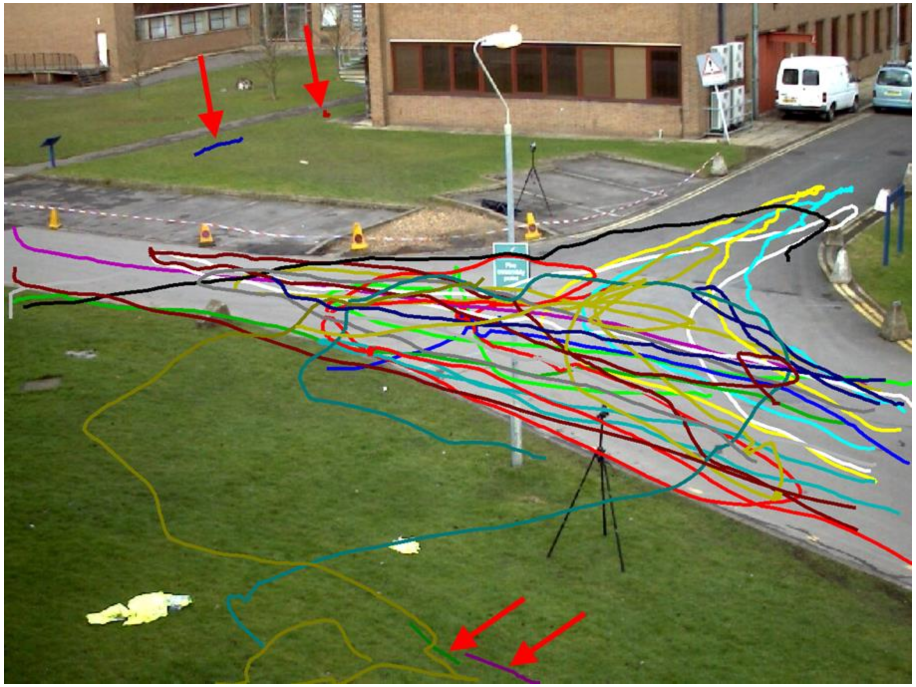


False negatives, false positives, and ID switches decrease!

CLEAR MOT scores

Qualitative Results

Remaining Issues



- Some false positive initializations at wrong scales…
  - Due to limited scale range of the person detector.
  - Due to boundary effects of the person detector.

References and Further Reading

- A good tutorial on Particle Filters
  - M.S. Arulampalam, S. Maskell, N. Gordon, T. Clapp. A Tutorial on Particle Filters for Online Nonlinear/Non-Gaussian Bayesian Tracking. In *IEEE Transactions on Signal Processing*, Vol. 50(2), pp. 174-188, 2002.

- The CONDENSATION paper
  - M. Isard and A. Blake, CONDENSATION - conditional density propagation for visual tracking, IJCV 29(1):5-28, 1998