Contour Tracking

Contour Tracking by Stochastic Propagation of Conditional Density

by Michael Isard and James Blake, in ECCV 1996

Introduction

- **Problem**: Track a curve X as it evolves over time given observations Z

- **Particle filter idea**: Stochastically approximate the state posterior p(X|Z) with a set of weighted particles and select argmax p(X|Z)

- **ConDensAtion**: Conditional Density propagAtion

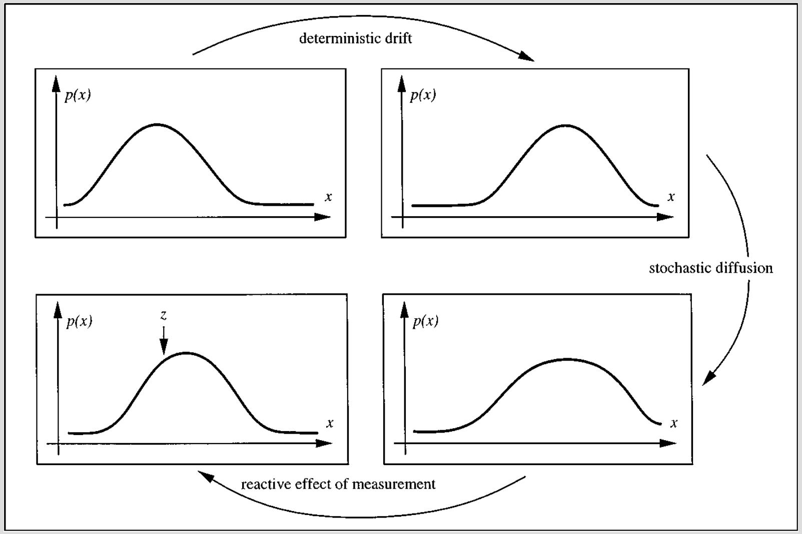
Plan

- Advantage of the Condensation Filter
- Factored Sampling
- Discrete-Time Propagation of State Density
- The Condensation Algorithm
- Shape Modelling
- Examples

Advantage of the Condensation Filter

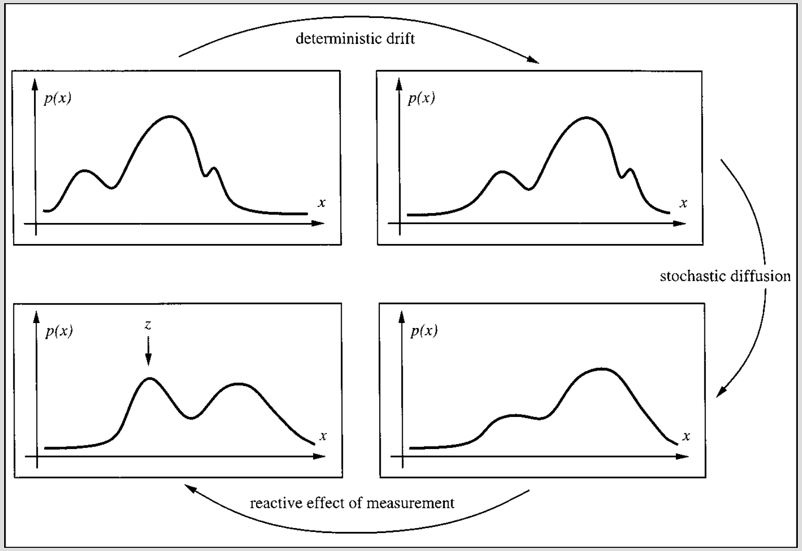
- Kalman Filter:

  Gaussian densities



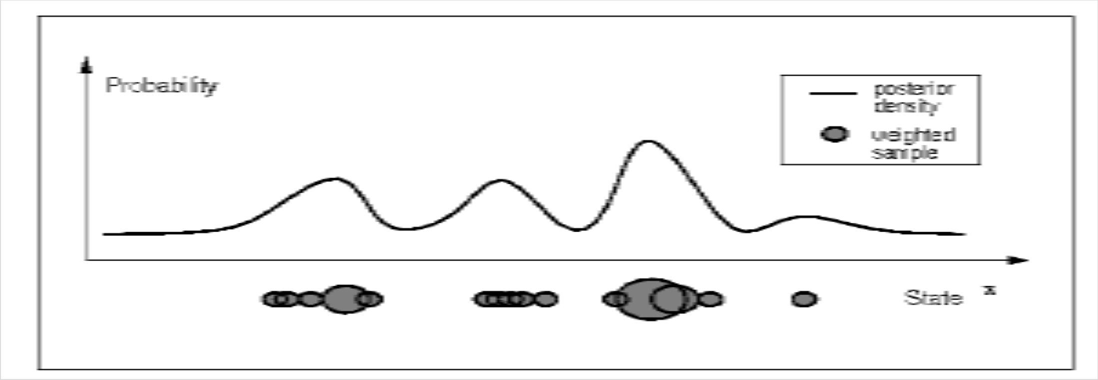
- Condensation Filter:

  Multi-modal densities



Factored Sampling

- Generate a set of samples that approximates the posterior p(X|Z)
- $p(X|Z) = k\,p(Z|X)p(X)$
- Sample set $s = \{s^{(1)},...,s^{(N)}\}$ generated from p(X)
- Weight for each particle: $\pi^{(i)} = K\,p(Z|s^{(i)})$



Discrete-Time Propagation of State Density

- Notation
- Stochastic dynamics
- Measurement
- Propagation

Discrete-Time Propagation of State Density

- Notation
  - x_t: state vector, $\mathbf{X_t}$: history of x_t
  - z_t: measurement feature vector, $\mathbf{Z_t}$: history of z_t
  - $p(x)$: prior probabilty of state vector
  - $p(z)$: probabilty of measuring z
  - $p(z|x)$: probability of measuring z given that the state is x
  - $p(x|z)$: probabilty of x given that measurement z has occurred
  - Bayes's rule: $p(x|z) = p(z|x)p(x) / p(z)$
  - Independence of probabilities: $p(AB) = p(A)p(B)$

Discrete-Time Propagation of State Density

- Stochastic dynamics
  - **Assumption**: temporal Markov chain
  - The new state depends only on the preceding state

$$p(x_t|\mathbf{X}_{t-1}) = p(x_t|x_{t-1})$$

Discrete-Time Propagation of State Density

- Measurement
  - **Assumption**: observations are independent with respect to the dynamical process

$$p(\mathbf{Z}_{t-1}, x_t | \mathbf{X}_{t-1}) = p(x_t | \mathbf{X}_{t-1}) p(\mathbf{Z}_{t-1} | \mathbf{X}_{t-1})$$

  - **Assumption**: observations are independent mutually

$$p(\mathbf{Z}_{t-1} | \mathbf{X}_{t-1}) = \prod_i p(z_i | x_i)$$

$$p(\mathbf{Z}_{t-1}, x_t | \mathbf{X}_{t-1}) = p(x_t | \mathbf{X}_{t-1}) \prod_i p(z_i | x_i)$$

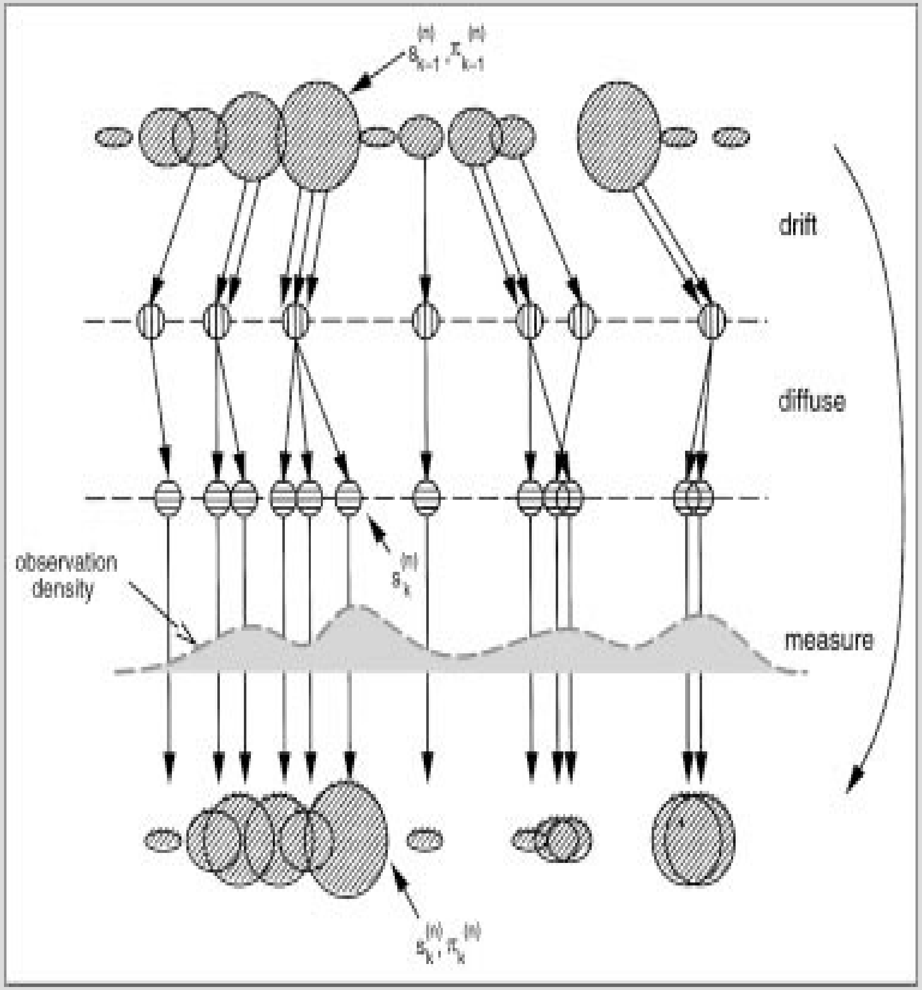
Discrete-Time Propagation of State Density

- Propagation

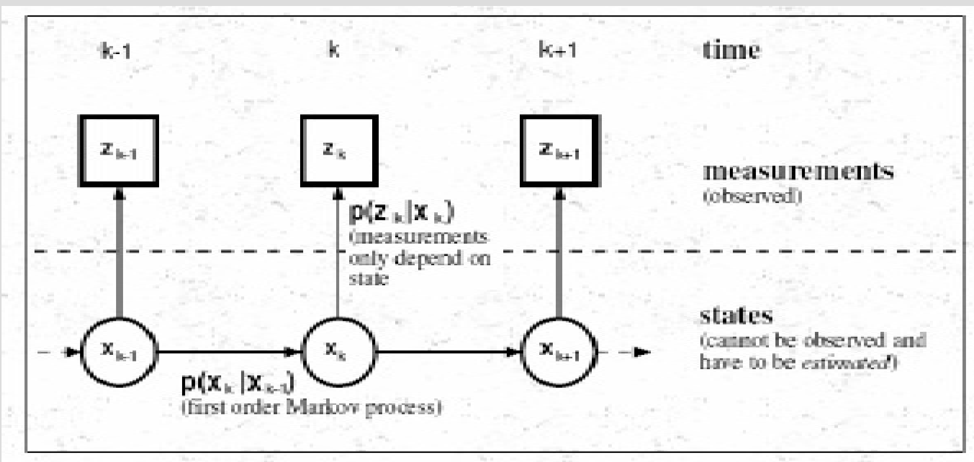
$$p(x_t|z_t) = k_t p(z_t|x_t)p(x_t|\mathbf{Z}_{t-1})$$

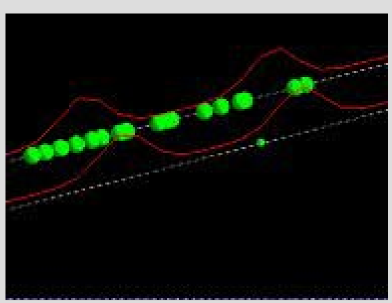
The Condensation Algorithm

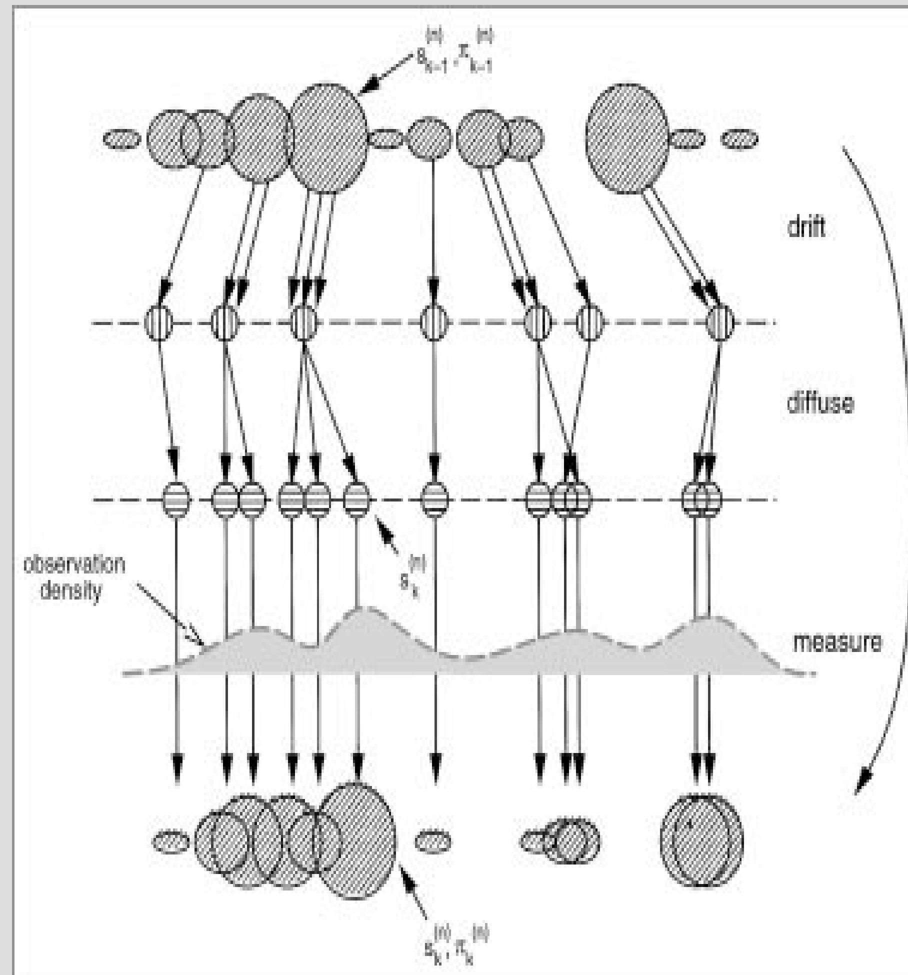
- **1. Select:** N particles from $\{s_{t-1}^{(n)}\}$ (*factored sampling*)
- **2. Predict:** move particles (*drift*) then perturb individually (*diffuse*)
- **3. Measure:** update weight according to image's local appearance to obtain $\{s_t^{(n)}, \pi_t^{(n)}\}$



The Condensation Algorithm







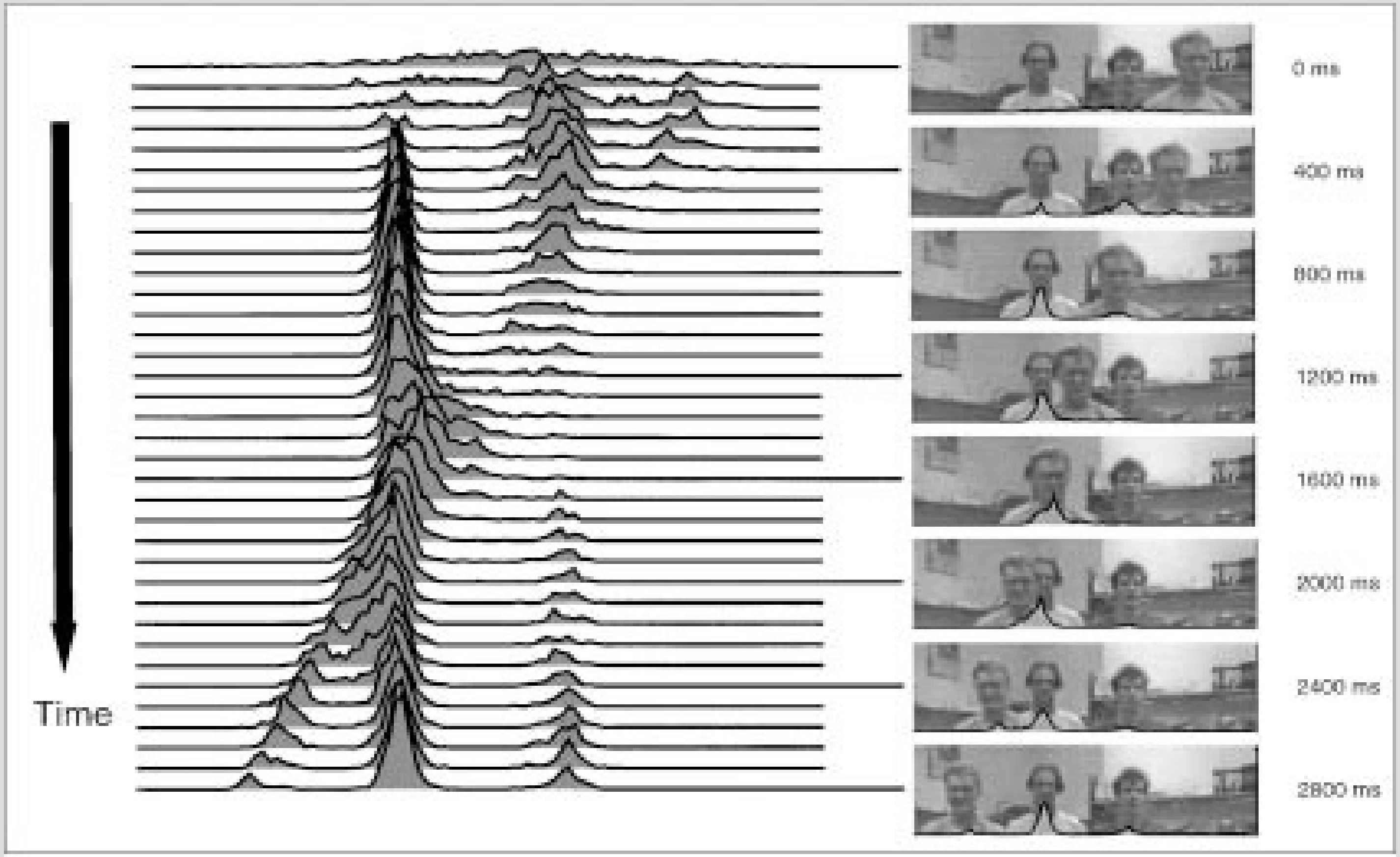
Shape Modelling

- State vector: $x = (x_c, y_c, \Theta, s)$
  - x_c, y_c,: position
  - Θ: angle of rotation
  - s: scale

- Dynamical model: $x_t = Ax_{t-1} + Bw_{t-1}$

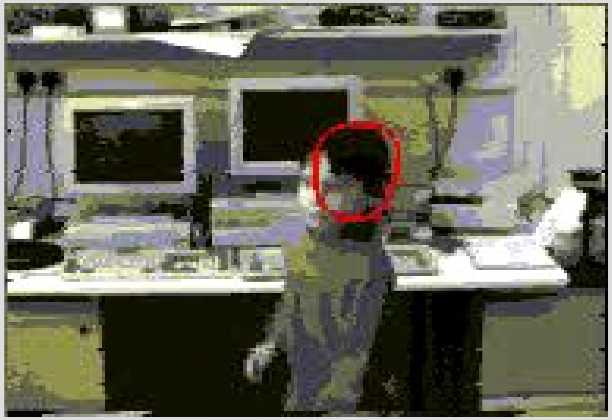
Examples

- Tracking a multi modal distribution



Examples

- Tracking a multi modal distribution
  - Tracking rapid motions through clutter



  - Tracking a leaf against similar leaves

Examples

- Tracking complex jointed objects