Particle Filtering

Ph.D. Coursework: Computer Vision

Eric Lehmann

Department of Telecommunications Engineering
Research School of Information Sciences and Engineering
The Australian National University, Canberra
Eric.Lehmann@anu.edu.au

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Context

Tracking:

- Probabilistic inference about the motion of an object given a sequence of measurements
- **Applications**: robotics, multimedia, military, videoconferencing, surveillance, etc.
- **Computer vision**: vehicle tracking, human-computer interaction, robot localisation, etc.

In practice:

- Noise in measurements (images)
- Background might be heavily cluttered

⇨ Robust tracking method: state-space approach

State-Space Approach

Problem definitions:

- State variable $\boldsymbol{\mathcal{X}}_k$: e.g. target position and velocity in state-space at time k

$$\boldsymbol{\mathcal{X}}_k = [x, y, z, \dot{x}, \dot{y}, \dot{z}]^T$$

- Observation $\boldsymbol{\mathcal{Y}}_k$: measurements obtained from processing camera image data

- Set of all observations: $\boldsymbol{\mathcal{Y}}_{1:k} = [\boldsymbol{\mathcal{Y}}_1, \ldots, \boldsymbol{\mathcal{Y}}_k]$

- System dynamics (transition) equation: $\boldsymbol{\mathcal{X}}_k = g(\boldsymbol{\mathcal{X}}_{k-1}, \boldsymbol{v}_{k-1})$

Aim: given all data $\boldsymbol{\mathcal{Y}}_{1:k}$, compute posterior PDF $p(\boldsymbol{\mathcal{X}}_k | \boldsymbol{\mathcal{Y}}_{1:k})$

⇨ Bayesian filtering problem

State-Space Approach

- **Bayesian filtering solution**: if posterior PDF $p(\boldsymbol{\mathcal{X}}_{k-1}|\boldsymbol{\mathcal{Y}}_{1:k-1})$ known at time $k-1$, compute current posterior PDF as follows:

Predict: $p(\boldsymbol{\mathcal{X}}_k|\boldsymbol{\mathcal{Y}}_{1:k-1}) = \int p(\boldsymbol{\mathcal{X}}_k|\boldsymbol{\mathcal{X}}_{k-1})\, p(\boldsymbol{\mathcal{X}}_{k-1}|\boldsymbol{\mathcal{Y}}_{1:k-1})\, \mathrm{d}\boldsymbol{\mathcal{X}}_{k-1}$

Update: $p(\boldsymbol{\mathcal{X}}_k|\boldsymbol{\mathcal{Y}}_{1:k}) \propto p(\boldsymbol{\mathcal{Y}}_k|\boldsymbol{\mathcal{X}}_k)\, p(\boldsymbol{\mathcal{X}}_k|\boldsymbol{\mathcal{Y}}_{1:k-1})$

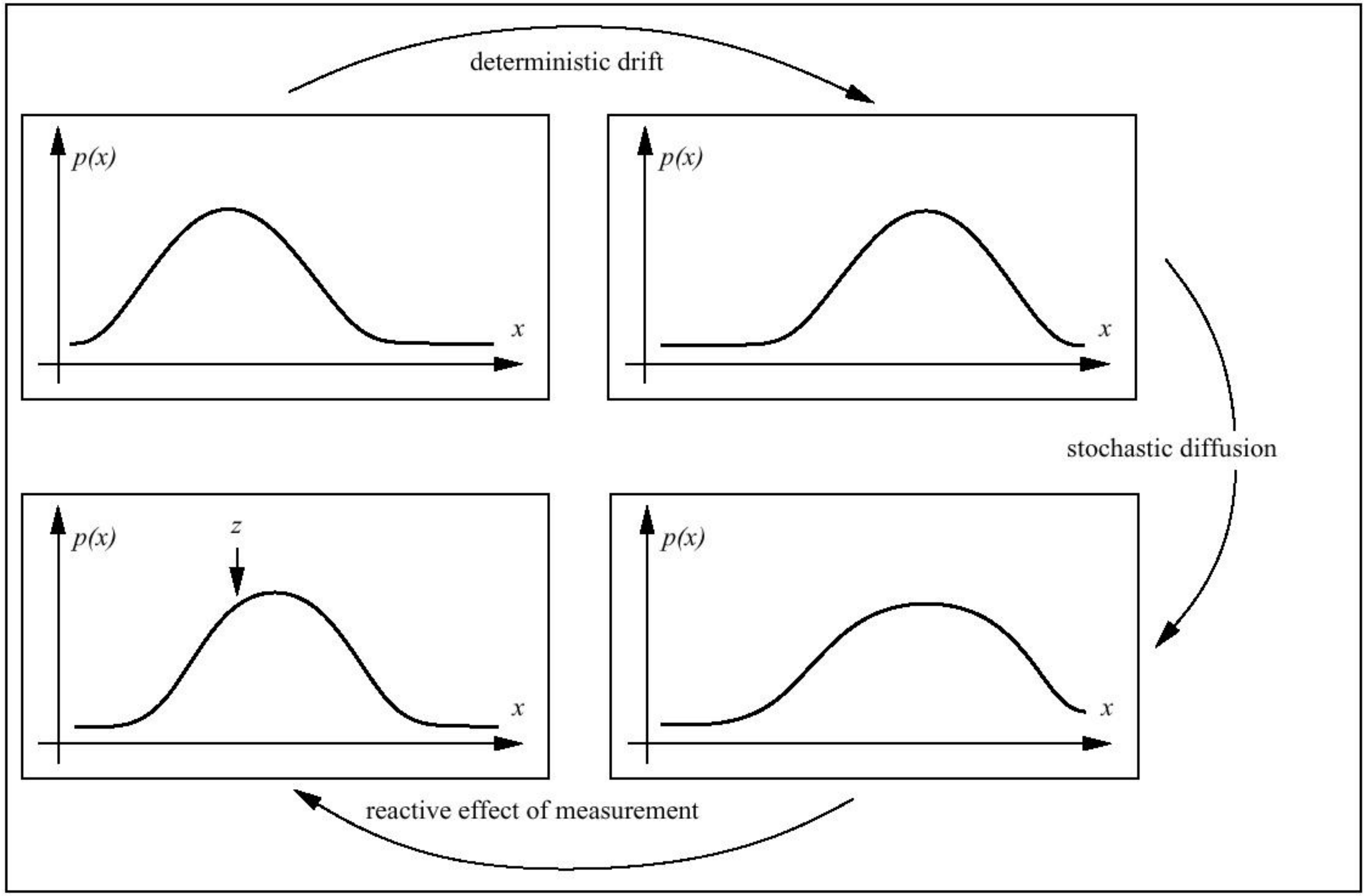
where $p(\boldsymbol{\mathcal{Y}}_k|\boldsymbol{\mathcal{X}}_k)$ is the likelihood function (measurement PDF)

- **Problem**: usually no closed-form solutions available for many natural dynamic models

- **Current approximations**: Kalman filter, extended Kalman filter, Gaussian sum methods, grid-based methods, etc.
  ⇨ Sequential Monte Carlo methods, i.e. Particle Filters (PF)

State-Space Approach: Symbolic Representation

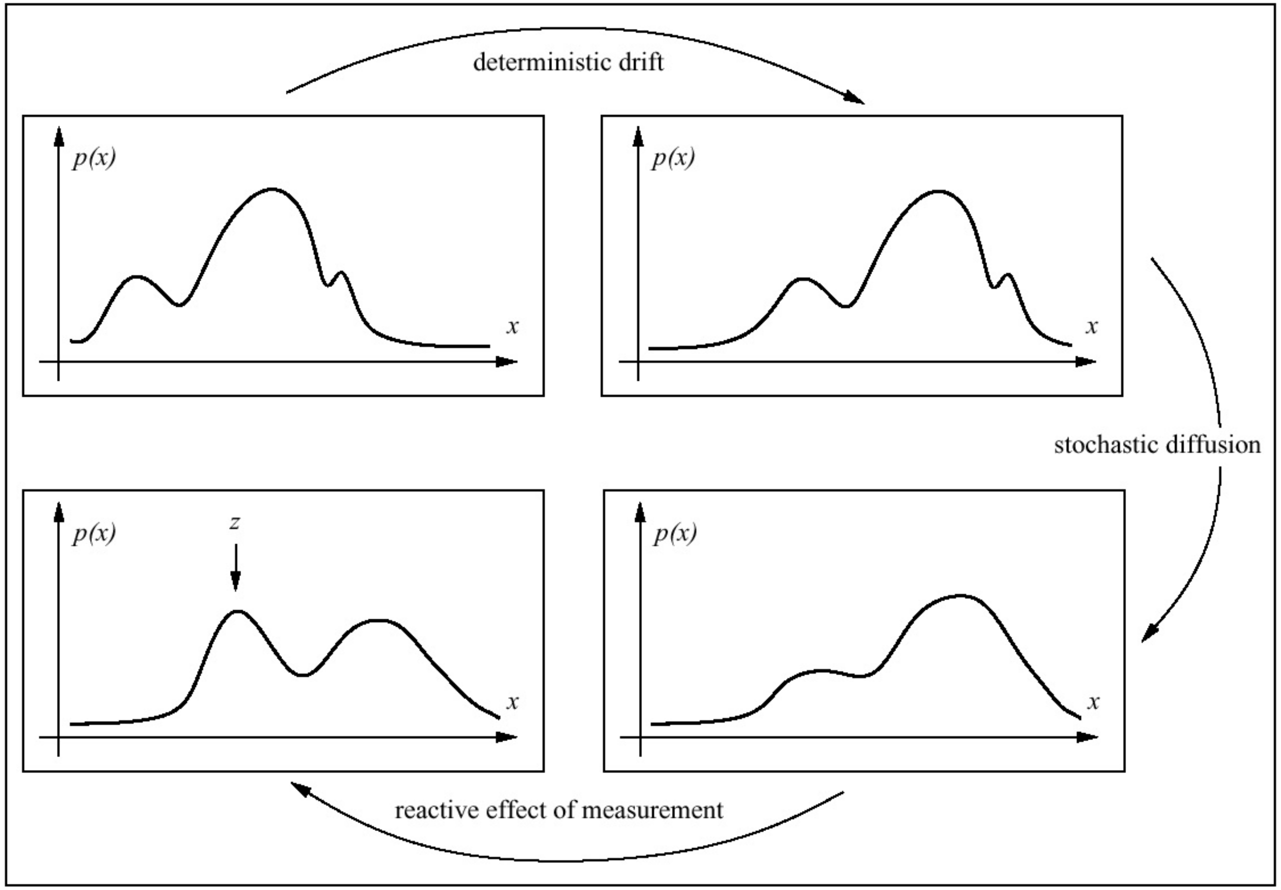
Case: Gaussian noise and linear equations



From [Condensation – conditional density propagation for visual tracking, **Isard and Blake**, *Int. J. Computer Vision*, 1998]

State-Space Approach: Symbolic Representation

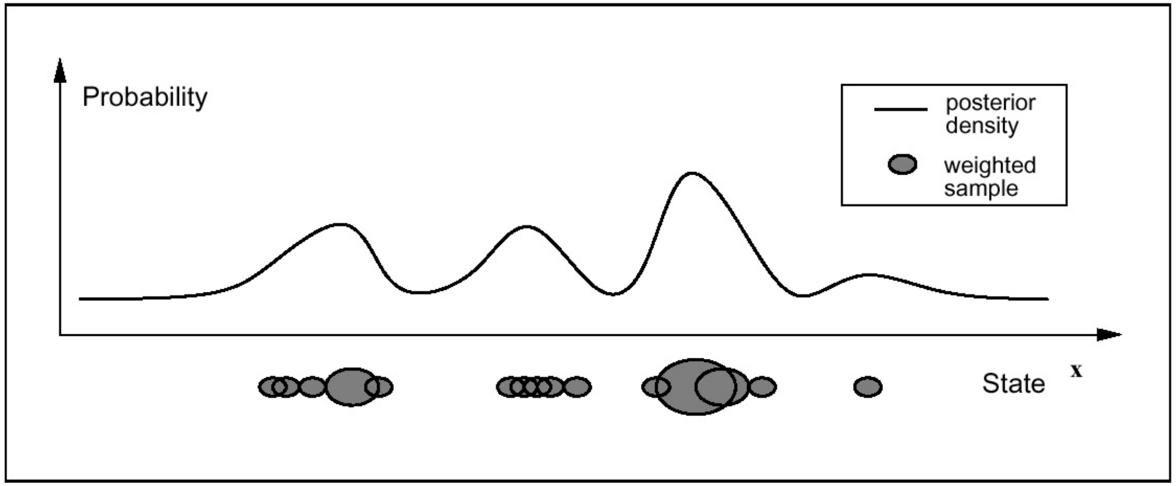
Case: non-Gaussian noise and/or nonlinear equations



From [Condensation – conditional density propagation for visual tracking, **Isard and Blake**, *Int. J. Computer Vision*, 1998]

Particle Filtering

- Numerical method to solve nonlinear and/or non-Gaussian Bayesian filtering problems
- Known variously as: bootstrap filtering, condensation algorithm, interacting particle approximations, survival of the fittest, JetStream, etc.
- Particle and weight representation of posterior density:



From [Condensation – conditional density propagation for visual tracking, **Isard and Blake**, *Int. J. Computer Vision*, 1998]

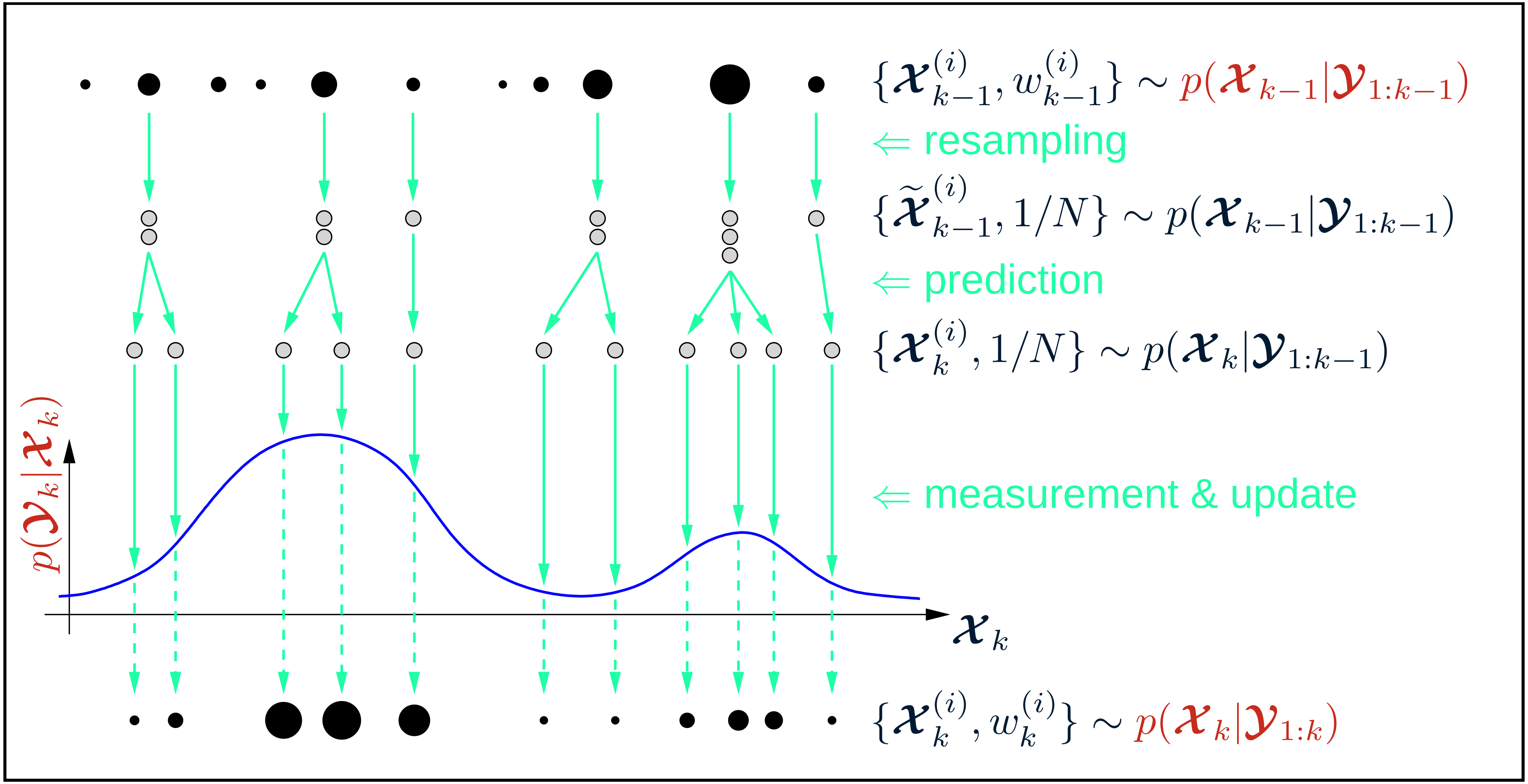
Basic PF Algorithm

From [Novel approach to nonlinear/non-Gaussian Bayesian state estimation, **Gordon et al.**, *IEE Proc. F.*, 1993]

Assumption: a set of N state samples and corresponding weights $\{\boldsymbol{\mathcal{X}}_{k-1}^{(i)}, w_{k-1}^{(i)}, i = 1, \ldots, N\}$ represents the posterior density $p(\boldsymbol{\mathcal{X}}_{k-1}|\boldsymbol{\mathcal{Y}}_{1:k-1})$ at time $k-1$

Procedure: update the particle set to represent the posterior density $p(\boldsymbol{\mathcal{X}}_k|\boldsymbol{\mathcal{Y}}_{1:k})$ for current time k according to following iterations

Basic PF: Symbolic Representation



PF Methods Overview

- Algorithm design choices:
  - ▷ **Source dynamics model**: various models available
  - ▷ **Observations**: camera image data
  - ▷ **Likelihood function**: derived from observations

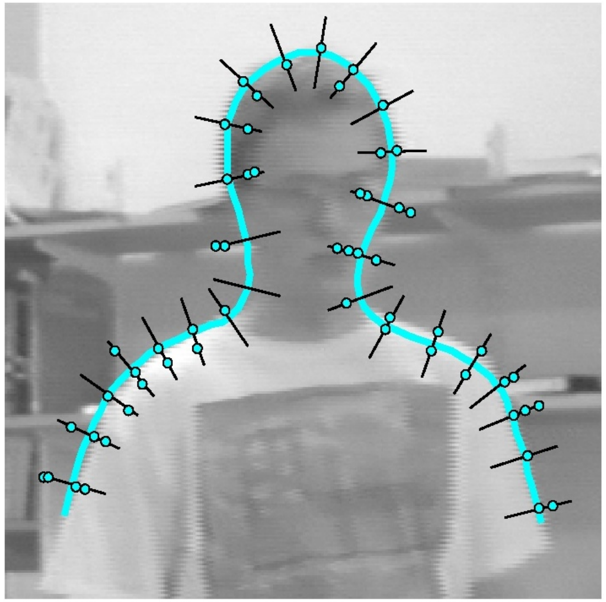
- Large number of enhanced PF versions to be found in literature: auxiliary PF, unscented PF, ICondensation, hybrid bootstrap, fast weighted bootstrap, annealed PF, etc.

- PF methods: special case of Sequential Importance Sampling, see [On sequential Monte Carlo sampling methods for Bayesian filtering, **Doucet et al.**, *Statist. Comput.*, 2000]

- Excellent review of current PF methods in [A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian Tracking, **Arulampalam et al.**, *IEEE Trans. Sig. Proc.*, 2002]

PF Tracking of a Head Outline

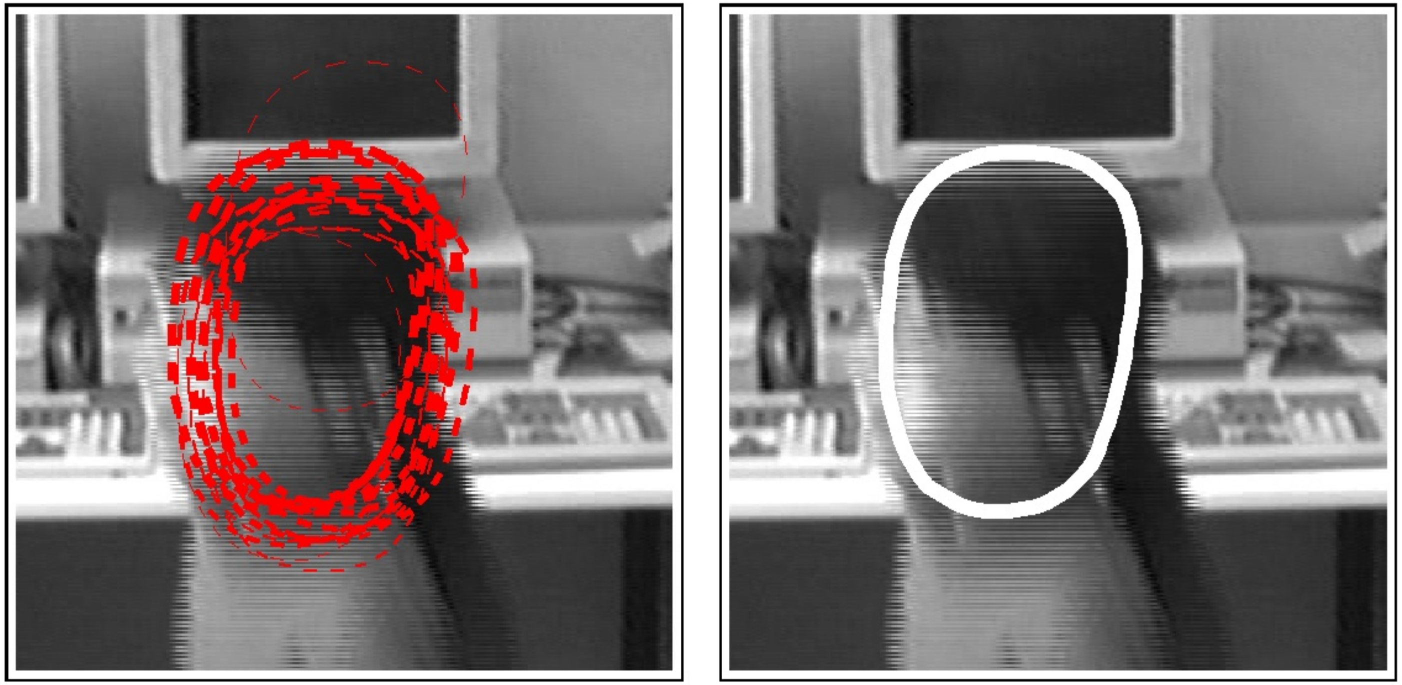
Standard head outline template (parametric spline curve) used for tracking. Measurements are obtained by detecting maxima of intensity gradient along lines normal to the head contour.



From [Condensation – conditional density propagation for visual tracking, **Isard and Blake**, *Int. J. Computer Vision*, 1998] and [Sequential Monte Carlo fusion of sound and vision for speaker tracking, **Vermaak et al.**, *Proc. Int. Conf. on Computer Vision*, 2001]

PF Tracking of a Head Outline

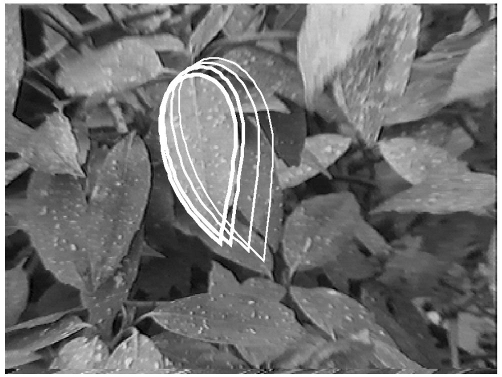
Particle representation of shape distribution



From [Condensation – conditional density propagation for visual tracking, **Isard and Blake**, *Int. J. Computer Vision*, 1998]

Application Example

Tracking objects in heavy clutter

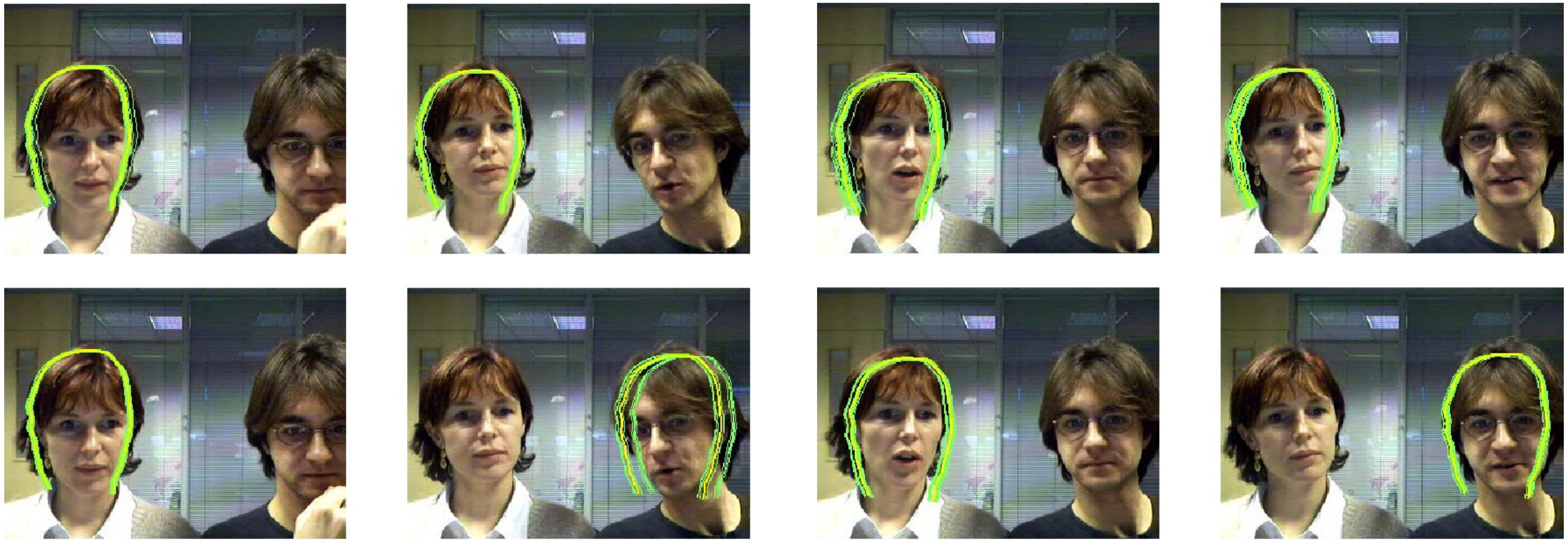


`hand.mpg` `dancemv.mpg` `leafmv.mpg`

From [Condensation – conditional density propagation for visual tracking, **Isard and Blake**, *Int. J. Computer Vision*, 1998]

Application Example

Combining sound and vision in PF algorithm

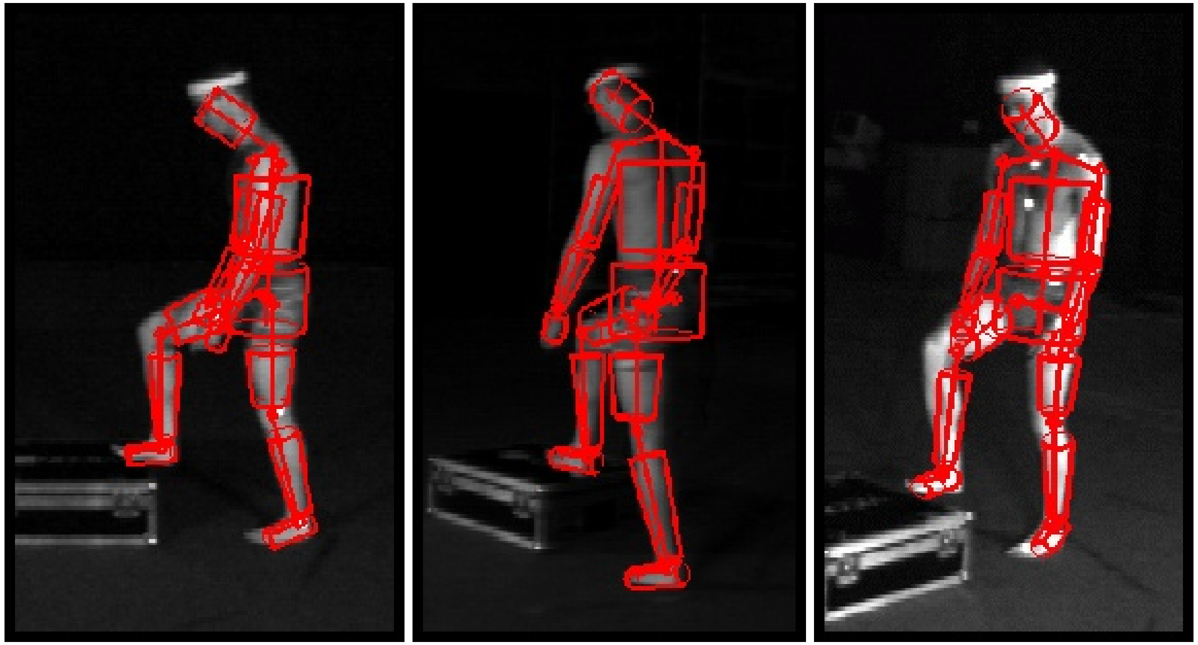


`pat_jacoC_out.avi`

From [Sequential Monte Carlo fusion of sound and vision for speaker tracking, **Vermaak et al.**, *Proc. Int. Conf. on Computer Vision*, 2001]

Application Example

Tracking of more complex models



`walker.mpg`

From [Articulated Body Motion Capture by Annealed Particle Filtering, **Deutscher et al.**, *IEEE Conf. Computer Vision and Pattern Recognition*, 2000]