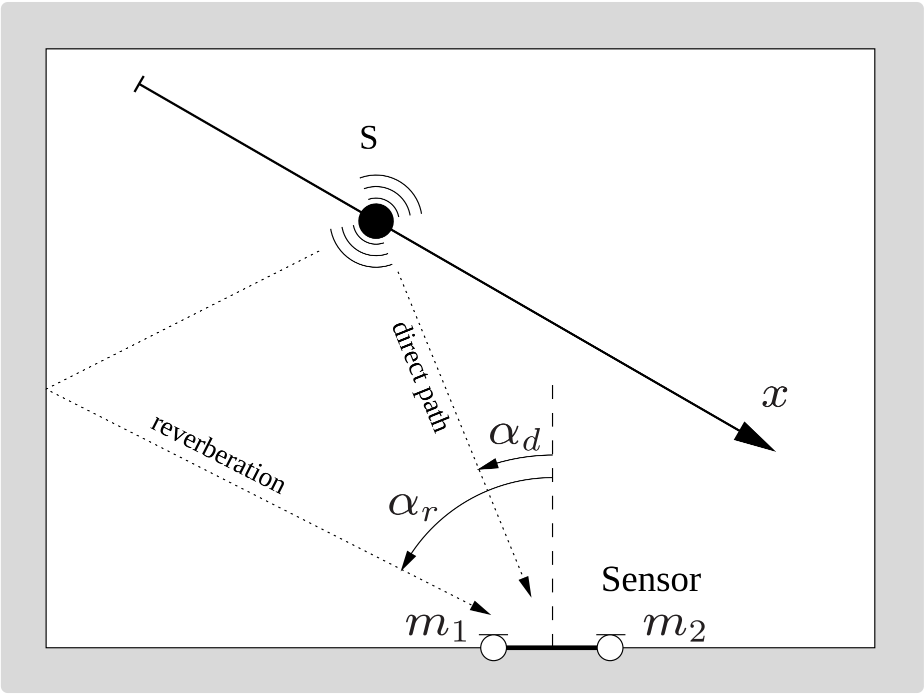
Acoustic source tracking in reverberant environments using particle filtering methods

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

February 4, 2002

Problem Description

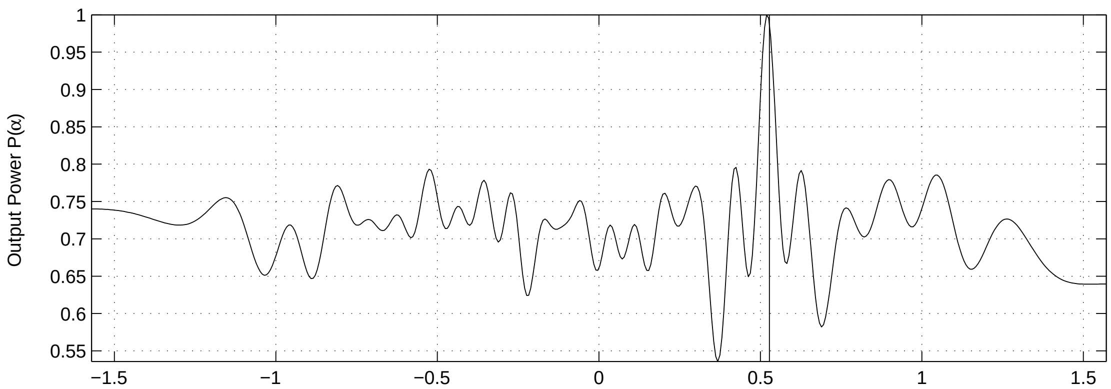
Aim: tracking of a moving acoustic source (for instance, a person talking) in a reverberant room. I.e. we would like to give an approximation of the source location at every time step, based on the information (observations) provided by a two-sensor microphone array.



Observations

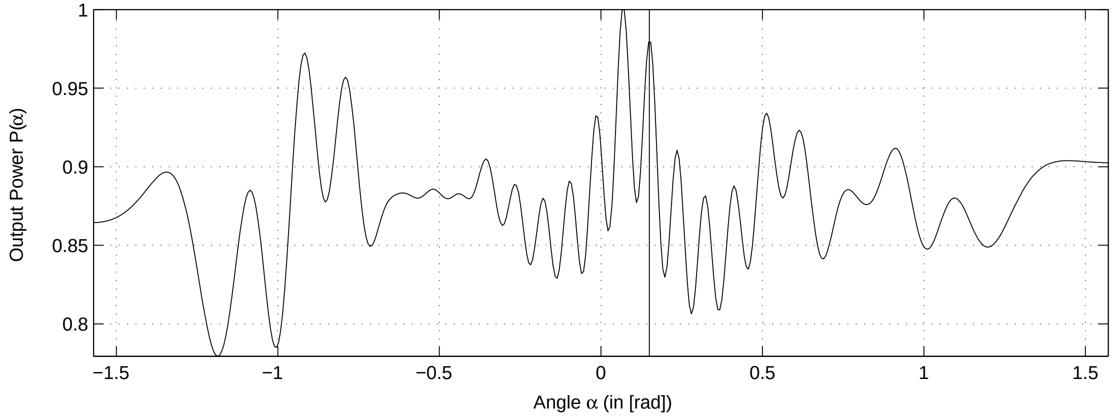
The microphone array measures the impinging acoustic power vs. angle of arrival with respect to its own orientation.

In an ideal case, it provides non-ambiguous information about the source position: the peak in the acoustic power measurement determines which angle the source is emitting from.



Major problem: reverberation

Due to several types of disturbance, the microphone array furnishes noisy (hence ambiguous) observations: which peak is to be associated with the true source?



Methods based on *time delay of arrival* measurements (peak picking) fail at even low levels of reverberation (90% failure for $T_{60} = 0.35$s).

⇒ **Alternative:** use of statistical methods instead (Bayesian framework).

Variable definitions

- State variable x_k: position of the source along the x-axis (the *state space*) at time index k.
- Observation y_k: data provided by the sensor (e.g. vector containing the angles of the 5 largest peaks in the power measurement) at time index k.
- Set of observations Y_k: set of all the measurements obtained up to time index k, i.e. $Y_k = \{y_i, i = 1, 2, \dots, k\}$.

$\Rightarrow$ At time step k, we want to compute the posterior density $p(x_k \mid Y_k)$, that is the probability of the state x_k given the set of all the observations y_i up to current time index k. This PDF contains *all* the information about the source position available at time k.

Statistical problem analysis

In a Bayesian problem, the posterior PDF can be computed as follows. Based on the transition density $p(x_k \mid x_{k-1})$ (derivable from the considered system equations), the prior density is defined as:

$$p(x_k \,|\, Y_{k-1}) = \int p(x_k \,|\, x_{k-1})\, p(x_{k-1} \,|\, Y_{k-1})\, dx_{k-1}\,. \tag{1}$$

The prior PDF is then updated with the observation likelihood $p(y_k \mid x_k)$ (also defined by the system under consideration) to obtain the desired posterior PDF:

$$p(x_k \,|\, Y_k) \propto p(y_k \,|\, x_k)\, p(x_k \,|\, Y_{k-1})\,. \tag{2}$$

Equations (1) and (2) constitute the general solution to the tracking problem (also known as *Bayesian filtering problem*).

$\Rightarrow$ **Problem:** Equations (1) and (2) are usually impossible to solve analytically, and hence impossible to compute practically!

Current solving methods

- Kalman filter: assumes a linear and Gaussian system model. In most of the practical applications however (like acoustic source tracking), the system under consideration is non-Gaussian and the different system equations involve nonlinearity.

- Extended Kalman filter: implements a linearisation of the nonlinear problem which may lead to poor results.

⇒ **Possible solution:** use of particle filtering methods.

What is particle filtering?

- Numerical method to solve nonlinear and/or non-Gaussian filtering problems.

- Uses an adaptive grid of N particles $x_k^{(i)}, i = 1, 2, \ldots, N$, (sample points) distributed over the state space, together with corresponding likelihood weights $\pi_k^{(i)}$. The set of particles and weights $\{(x_k^{(i)}, \pi_k^{(i)}), i = 1, 2, \ldots, N\}$ represents a random draw from the targeted posterior PDF $p(x_k | Y_k)$.

- The set of particles and weights $\{(x_k^{(i)}, \pi_k^{(i)}), i = 1, 2, \ldots, N\}$ is an approximation of the *true* posterior PDF. This approximation can be made arbitrarily accurate as $N \to \infty$.

- As a new observation becomes available online, the particle set at time k can be easily updated to form an approximation of the posterior PDF at time $k + 1$.

Particle filtering algorithm

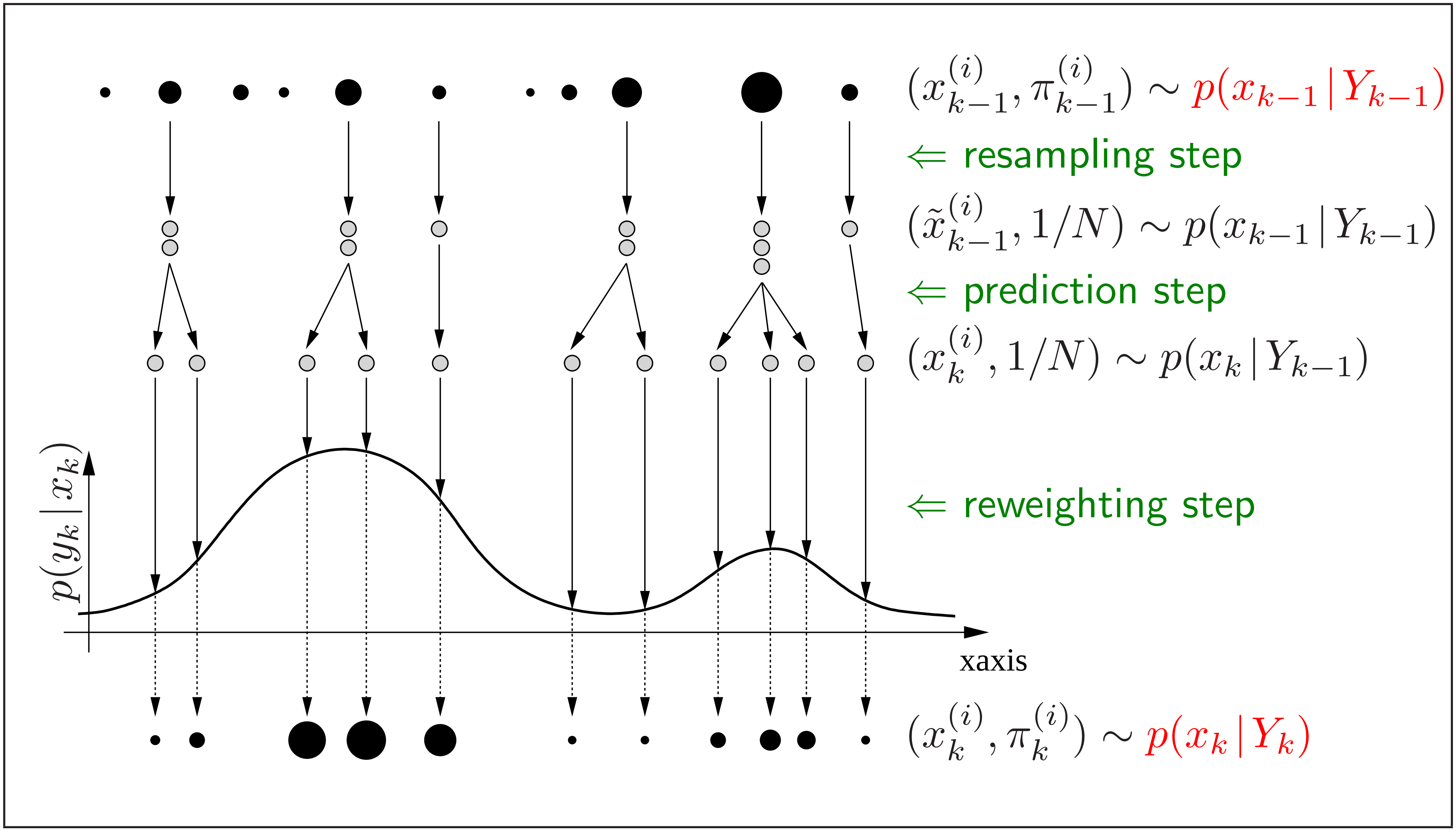
The basic particle filtering principle is based on the following three-step update of the particle set from one time index to the other:

1) **Prediction:** each particle is relocated in the state space depending on its current position and according to the source dynamics under consideration (defined by the system model).

2) **Reweighting:** a new likelihood weight is assigned to each particle based on the observation which becomes available from the sensor for the current time step.

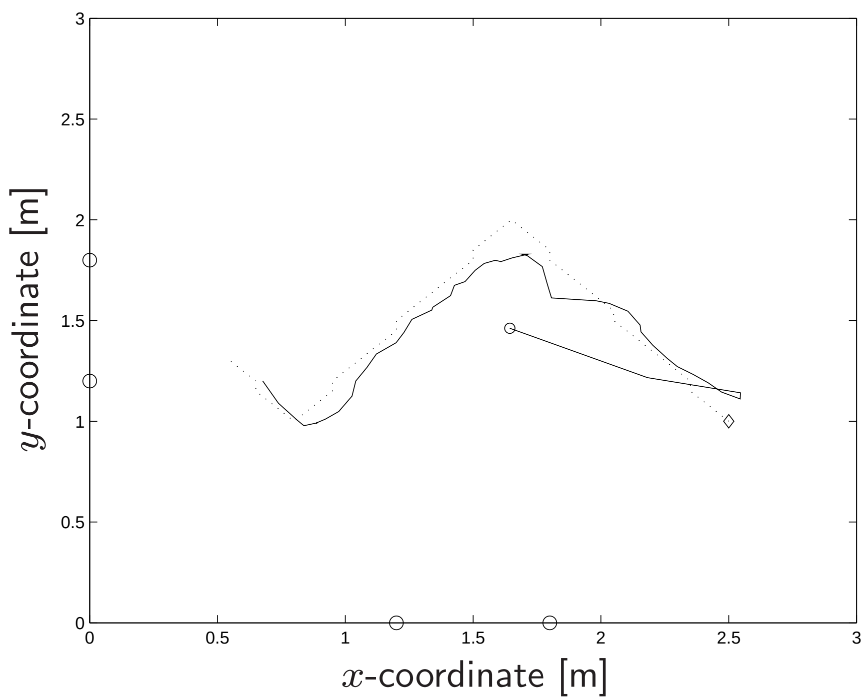
3) **Resampling:** the resulting set of particles is finally resampled N times according to the likelihood weights. The particles with low likelihood weights disappear (i.e. they are not selected during the resampling process) and reappear in areas of the state space where the likelihood shows higher values.

Symbolic representation



Simulation results

Tracking of a white noise source in a 3m by 3m room with reverberation time $T_{60} = 0.2$s. A four-sensor array is used to provide observations in two dimensions. The algorithm uses 50 particles which quickly lock on to the acoustic source and track it despite the reverberation (dashed line: source trajectory, solid line: average position of the particles).



Conclusions

- New method of dealing with online filtering problems.
- Suitable for nonlinear and non-Gaussian systems.
- Computationally inexpensive and easily implementable.
- Efficiently deals with noise and other disturbances.