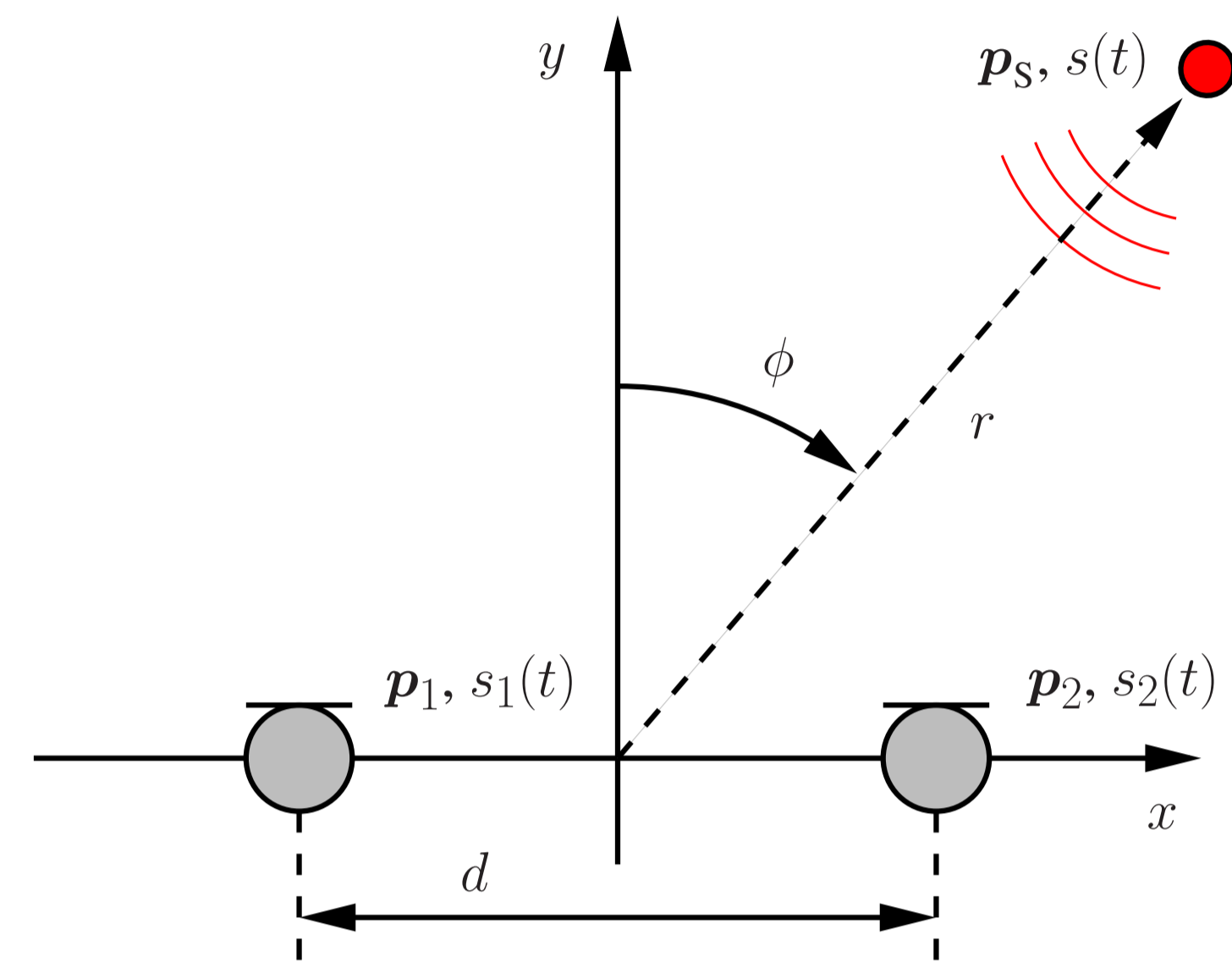


PARTICLE FILTERING APPROACH TO ADAPTIVE TIME-DELAY ESTIMATION

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Time-Delay Estimation (TDE)



$$s_1(t) = s(t) + \eta_1(t)$$

$$s_2(t) = \alpha \cdot s(t - \tau) + \eta_2(t)$$

with time difference of arrival (TDOA) $\tau \in \mathbb{R}$

Problem Definition

Noisy signals received at two spatially separated sensors:

- known sensor positions $\mathbf{p}_i = [x_i \ y_i]^T$, $i = 1, 2$
- unknown source signal $s(\cdot)$
- independent and uncorrelated (diffuse) noise $\eta_1(\cdot)$ and $\eta_2(\cdot)$
- time-varying TDOA τ (relative source-sensor motion)

Aim

Online estimate $\hat{\tau}$ of (subsample) TDOA τ using $s_1(t)$ and $s_2(t)$

State-State Approach

- State variable at time $k = 1, 2, \dots$: X_k
- Observation variable (measurement): Y_k
- Set of observations: $Y_{1:k} = \{Y_1, \dots, Y_k\}$
- Transition model:

$$X_k = g(X_{k-1}, u_k)$$

- Observation model:

$$Y_k = h(X_k, v_k)$$

where $g(\cdot)$ and $h(\cdot)$ are possibly nonlinear, u_k and v_k are possibly non-Gaussian

Bayesian Filtering

Compute *posterior* PDF $p(X_k|Y_{1:k})$, then estimate current state:

$$\hat{X}_k = \int X_k \cdot p(X_k|Y_{1:k}) dX_k$$

Bayesian Solution

Given $p(X_{k-1}|Y_{1:k-1})$, compute $p(X_k|Y_{1:k})$ recursively:

$$p(X_k|Y_{1:k-1}) = \int p(X_k|X_{k-1}) p(X_{k-1}|Y_{1:k-1}) dX_{k-1}$$

$$p(X_k|Y_{1:k}) \propto p(Y_k|X_k) p(X_k|Y_{1:k-1})$$

Problem

Bayesian recursion is only analytical for a small number of practical cases, e.g. Kalman filter (linear and Gaussian problems)

\Rightarrow need for efficient *approximation* techniques!

Particle Filtering (PF)

- Recursive approximation of the Bayesian filtering solution
- Discrete representation of the posterior PDF with N particles and weights:

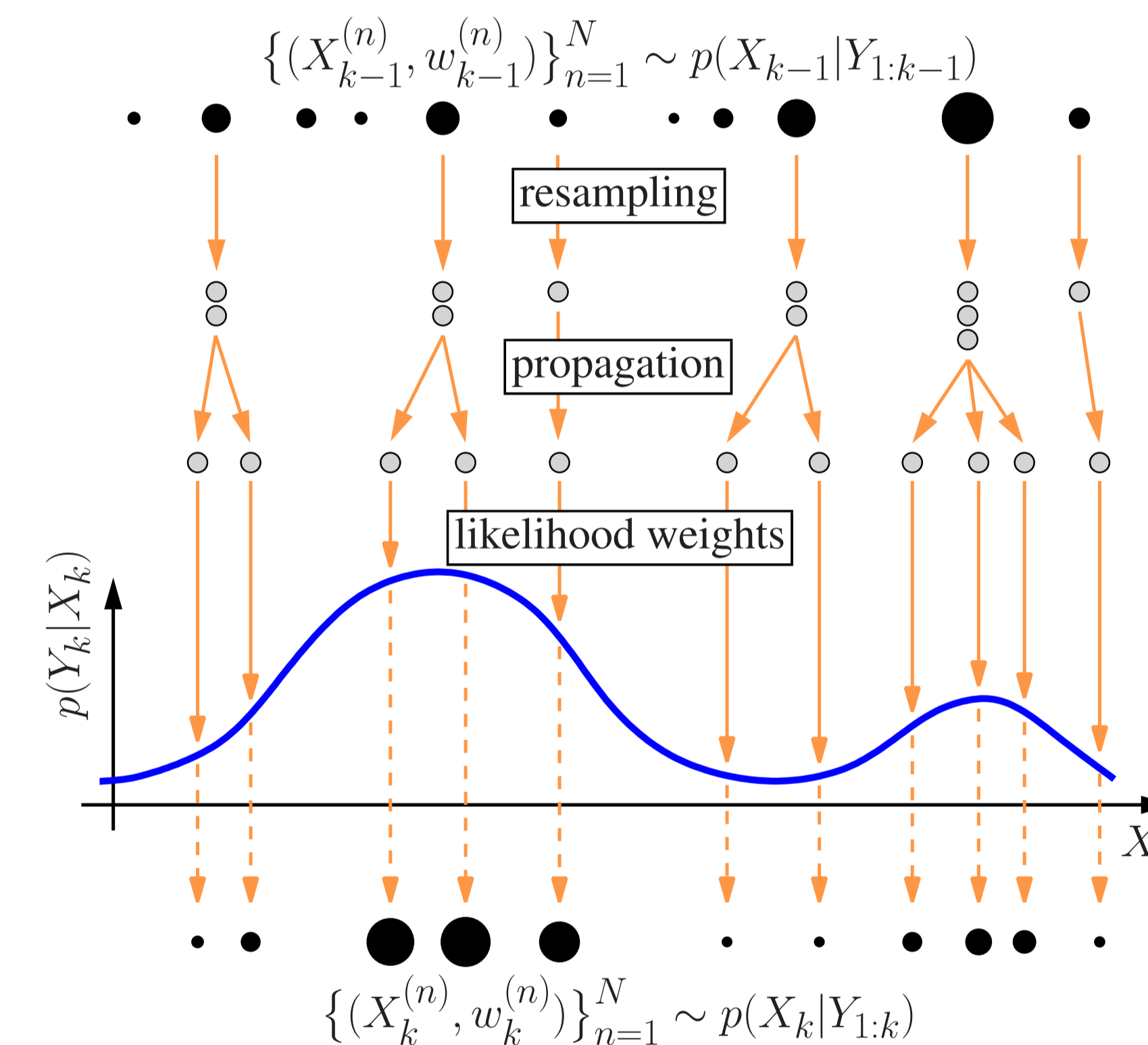
$$\{(X_k^{(n)}, w_k^{(n)})\}_{n=1}^N \sim p(X_k|Y_{1:k})$$

- Estimate of current state:

$$\hat{X}_k \approx \sum_{n=1}^N w_k^{(n)} X_k^{(n)}$$

- Applicable to nonlinear and/or non-Gaussian problems

PF Recursion



PF for Time-Delay Estimation

- State variable: $X_k \triangleq \tau_k$
- TDOA modeled as (truncated) FIR fractional-delay filter:

$$\mathbf{h}(k) = [h_{-P}(k) \ \dots \ h_0(k) \ \dots \ h_P(k)]^T$$

$$h_i(k) = \text{sinc}(i - \tau_k)$$

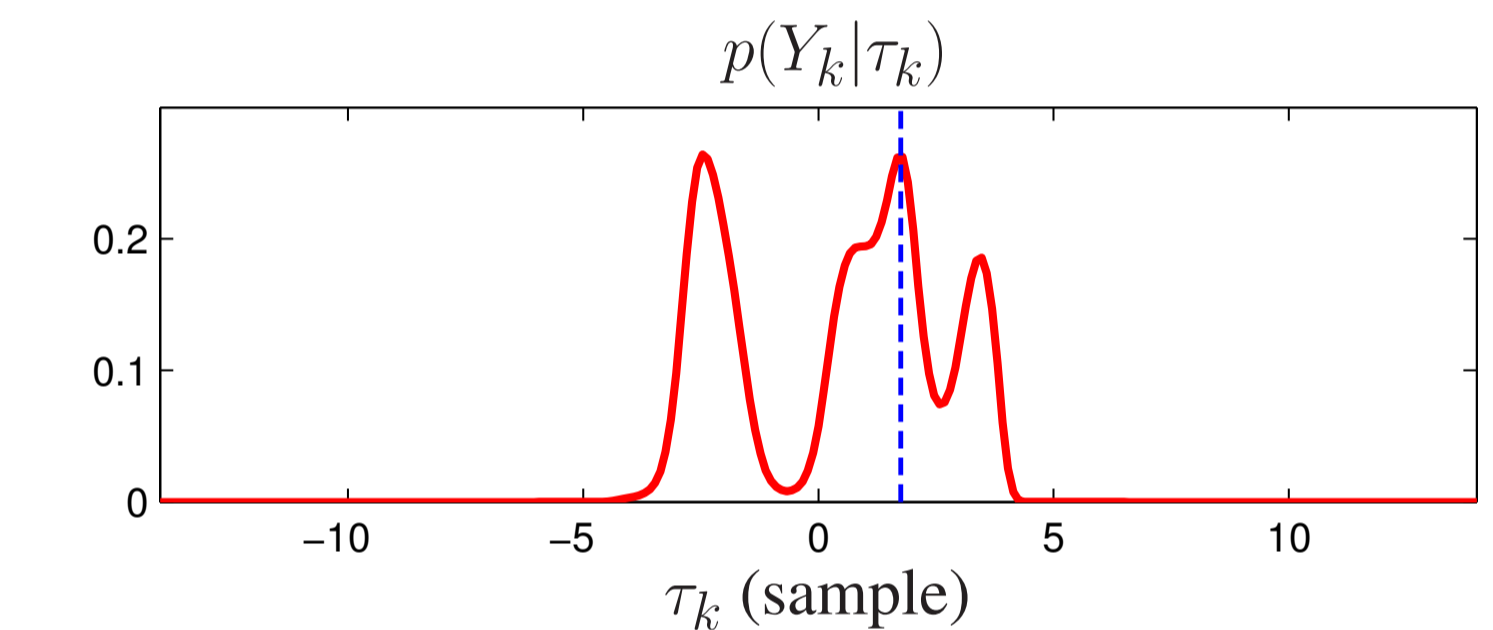
- Signal data collected in overlapping frames, for sensor $i = 1, 2$:

$$\mathbf{s}_i(k) = [s_i(k-2P) \ \dots \ s_i(k-P) \ \dots \ s_i(k)]^T$$

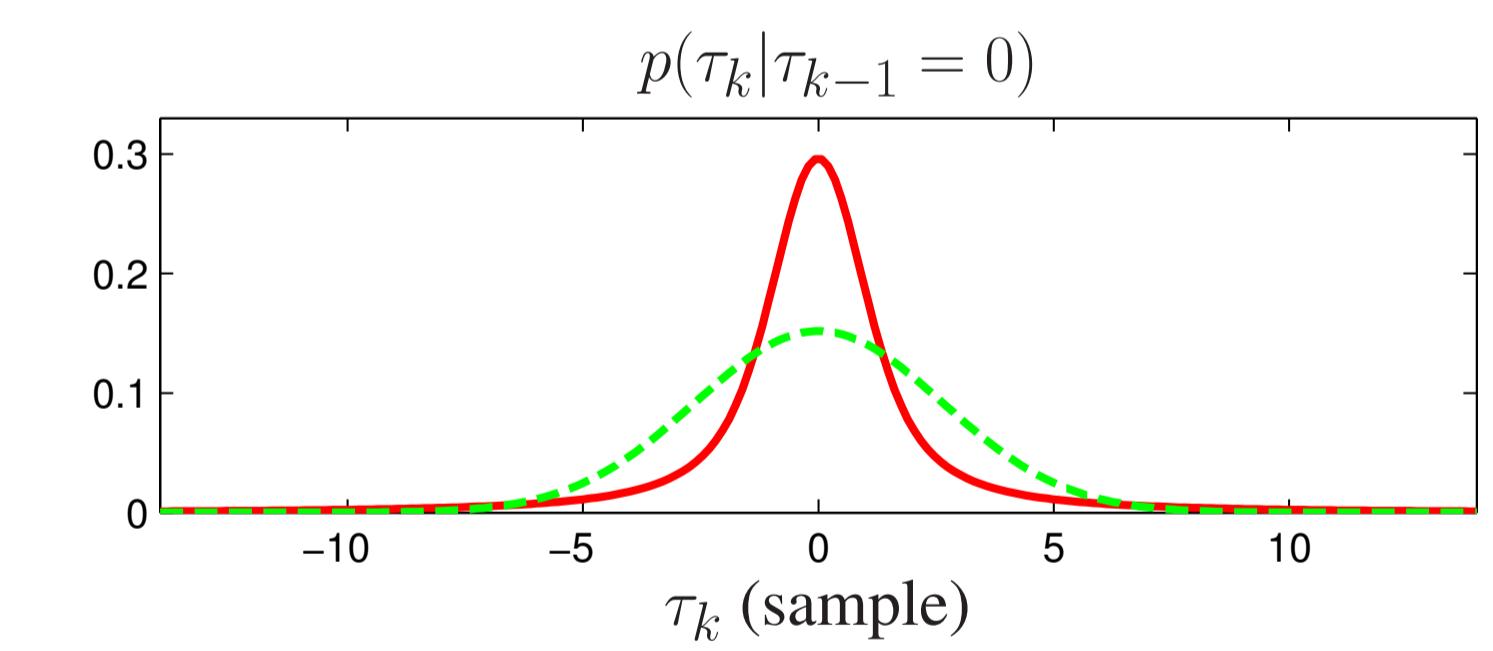
- *Likelihood function*. Observation defined as error between time-shifted signal values:

$$Y_k \triangleq s_2(k-P) - \mathbf{h}(k)^T \mathbf{s}_1(k)$$

Example likelihood function \Rightarrow multi-modal, non-Gaussian



- *Transition PDF*. Source motion modeled as random-walk, near-field or far-field, leads to non-Gaussian transition PDF



Advantages of Current Approach

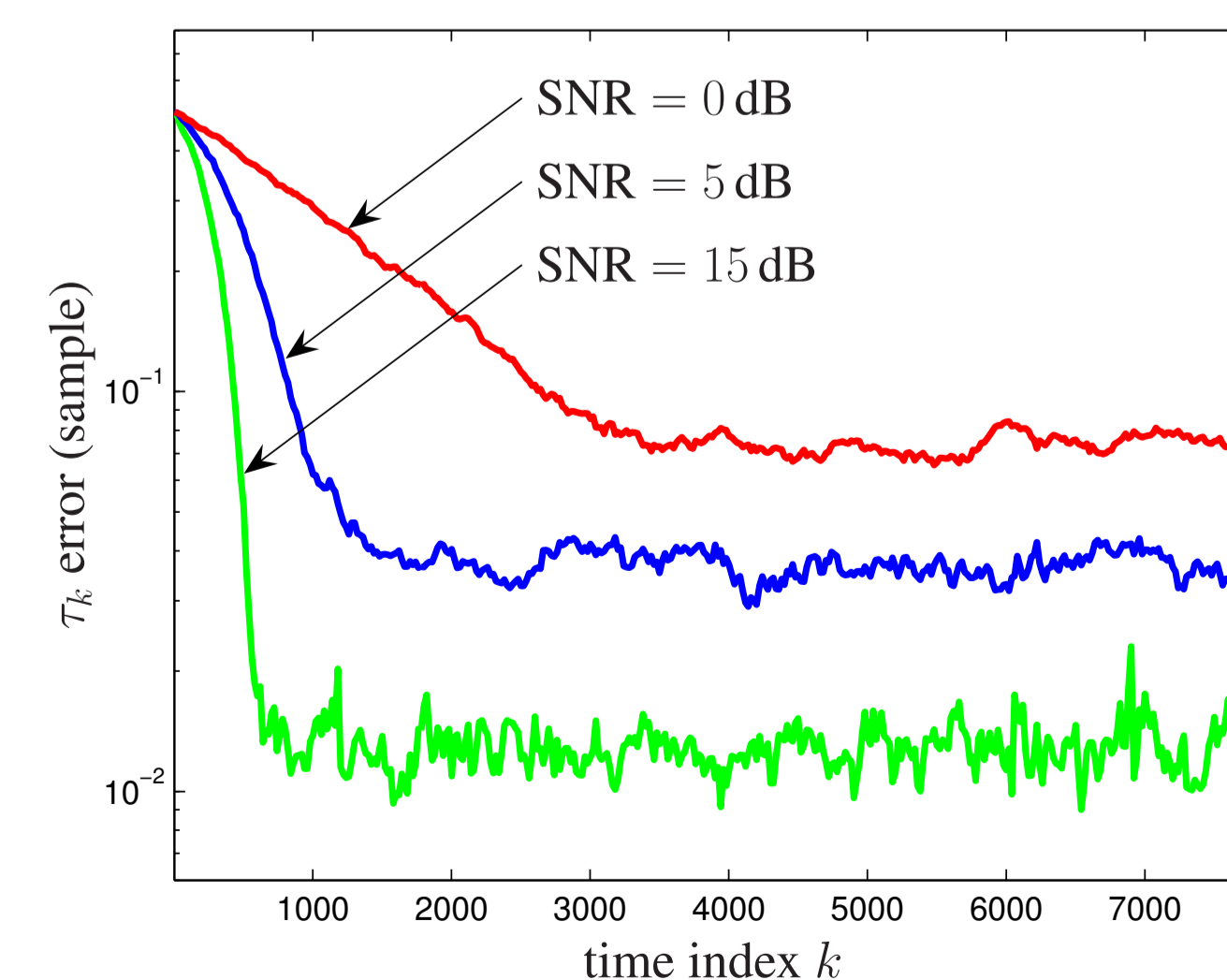
- Includes “dynamics model” of considered target’s time delay
- Can represent multi-modal PDFs (multiple hypotheses)
- In comparison to non-adaptive methods (e.g. GCC): no function maximization required, no interpolation to yield subsample time delays

Experimental Simulation Setup

- Fixed source position, i.e. constant TDOA
- $N = 50$ particles
- FIR filter length $2P + 1 = 51$
- Sampling frequency $f_s = 16$ kHz

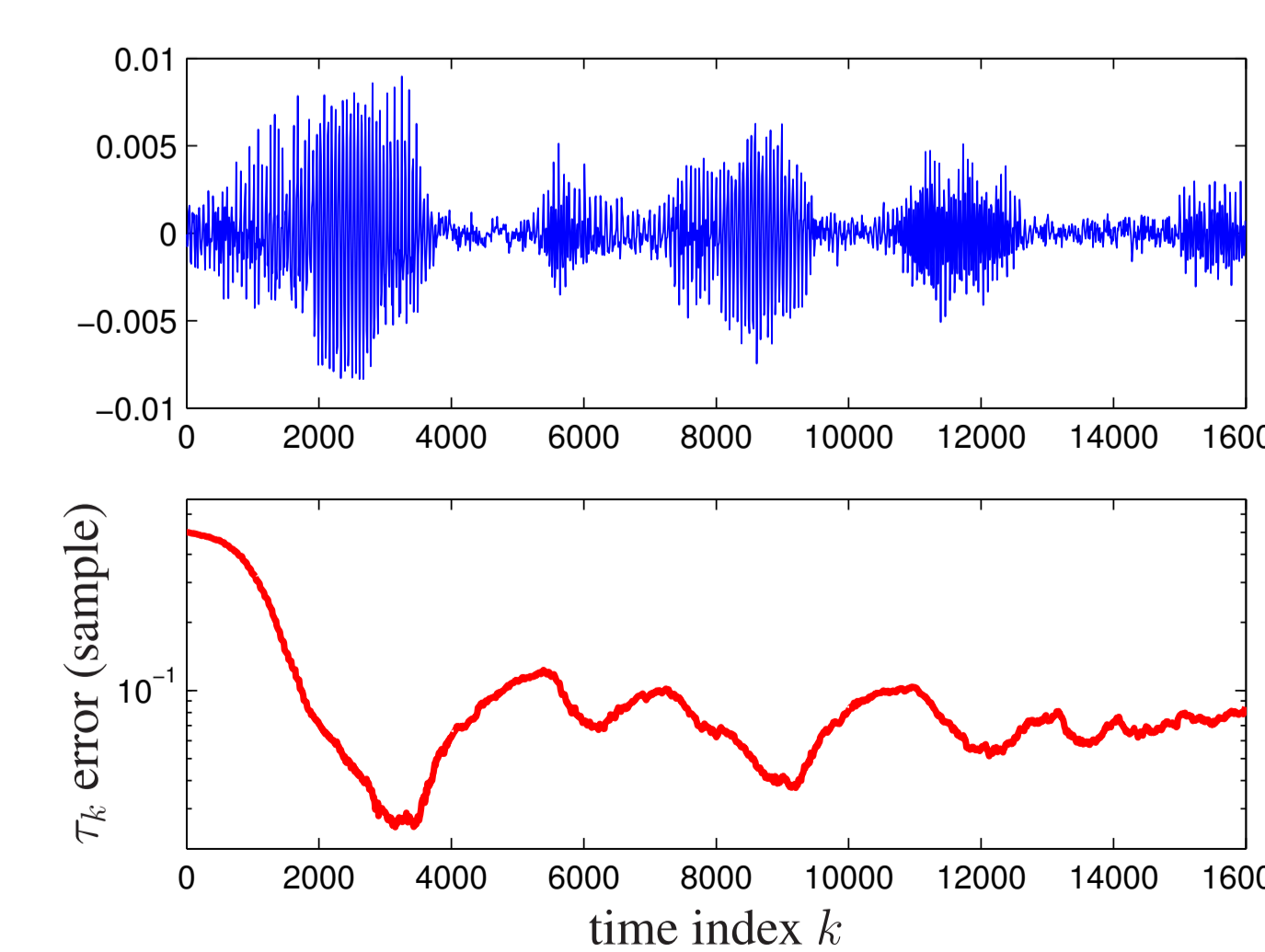
Simulation Results

PF results using stationary signal (white noise)



Simulation Results

Non-stationary (speech) signal @ 15 dB SNR



Conclusions

- PF well suited to handle non-Gaussian problem (e.g. compared to Kalman filter)
- Proposed method based on a sample-by-sample approach
- Preliminary simulation results show that proposed method is able to track correct TDOA with estimation error < 0.1 sample
- Method works with both stationary and speech signals

Future Work

- Assessment with real sound source (moving speaker)
- Assessment in real room situation (reverberation)
- Comparison with other TDE methods (e.g. LMS, ETDE, etc.)
- Include signal attenuation α in state variable