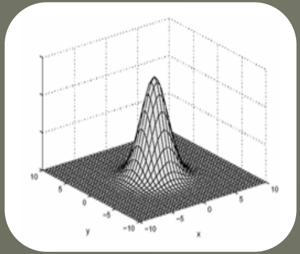
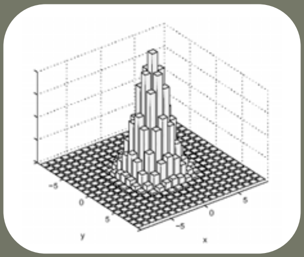
Target Tracking: Emerging Non-Linear Stochastic State Estimation Techniques

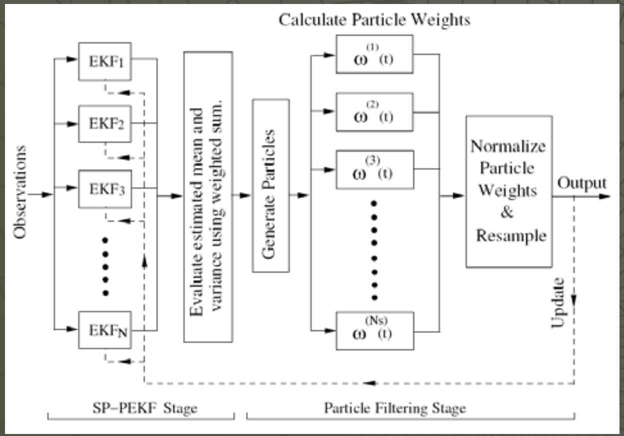




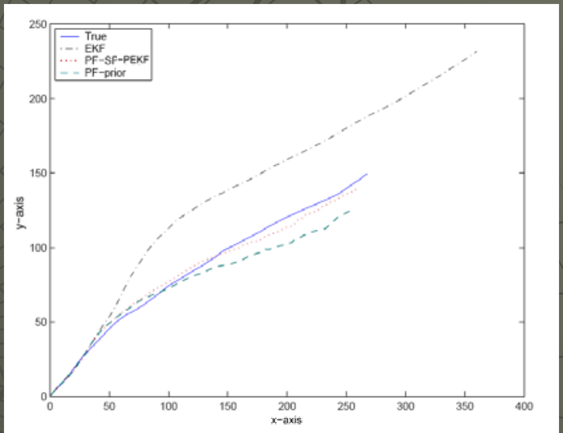
Tracking algorithms based on "particle filtering" provide improvements to areas that require the analysis of dynamic movements, particularly when the underlying dynamic models are non-linear and when the measurement noise is non-Gaussian. As discussed in the most recent literature, *particle filtering* is defined as an emerging Bayesian method based on sequential Monte-Carlo non-linear state estimation techniques.

$$\tilde{\omega}_t^{(i)} \propto \tilde{\omega}_{t-1}^{(i)} \frac{p(\mathbf{z}_t|\mathbf{x}_t^{(i)})p(\mathbf{x}_t^{(i)}|\mathbf{x}_{t-1}^{(i)})}{q(\mathbf{x}_t^{(i)}|\mathbf{x}_{0:t-1}^{(i)},\ \mathbf{z}_{1:t})}$$

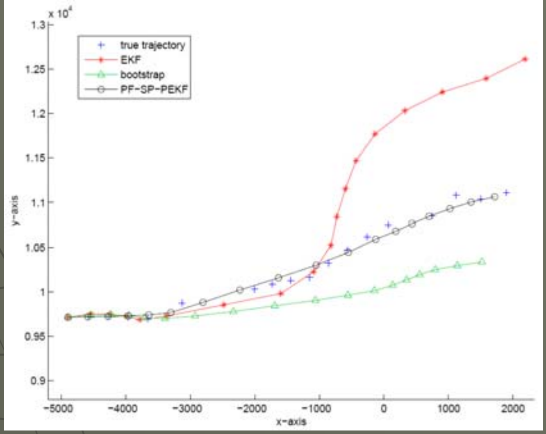
Left: Filtering Block Diagram



Middle: Example 1



Right: Example 2



Why is particle filtering important for tracking?

1. *Tracking in the presence of strong maneuvers. When the object makes a sharp change in course, conventional techniques (such as the Extended Kalman Filter) cannot maintain track.*
2. *One step ahead prediction algorithms for optimum beam-steering– superseding track while scan in the future.*

As typically done, the Kalman filter or the extended Kalman filter is employed for data fusion and tracking of targets (either point target or distributed). Particle filters will offer greater accuracy in their tracking particularly when the dynamic movements are modeled by non-linear processes, because the underlying posterior probability distributions of the state variables are calculated in real-time without prohibitive Gaussian assumptions – something that Kalman based techniques do not.

OU Contact: M. Yeary