PILOT: An Actor-oriented Learning and Optimization Toolkit for Swarm Applications

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Motivation

- Distributed system design is prone to errors:
  - time and concurrency often not addressed by programming abstractions
  - algorithm design is not compositional
- In a mobile sensor network setting, design requirements are even more complex
- Existing software abstractions based on imperative code fall short on providing
  - Scalability
  - Structured, repeatable code for deterministic behavior
  - Flexible interfaces for variable computational resources

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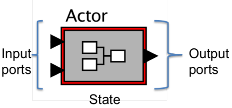
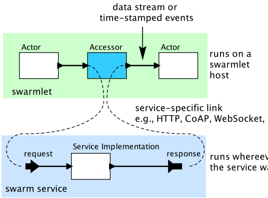
Introduction

- We present PILOT (Ptolemy Inference, Learning, and Optimization Toolkit) that presents an actor library for structured design of robotic sensor network applications
- **Goal:** Designing sensor-to-actuator learning and control applications for robotic sensor networks
- Reusable, **actor-oriented component abstractions** that are less error-prone and can be deployed on variable network resources
- Inference and optimization tasks can be defined by the state-space model of the problem domain

Actor-Oriented Design

- Ptolemy II
  - Ptolemy II is an open source platform for modeling and simulation of systems.
  - Actor-oriented, hierarchical, heterogeneous design for composing models of computation
  - Accessors: Actors that provide access to sensors, actuators and remote services
- The Decorator design pattern
  - PILOT utilizes the `decorator` design pattern based on Ptolemy to define hierarchical association relations between state-space and measurement models
- Accessors: Actors that provide access to sensors, actuators and remote services





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System Architecture

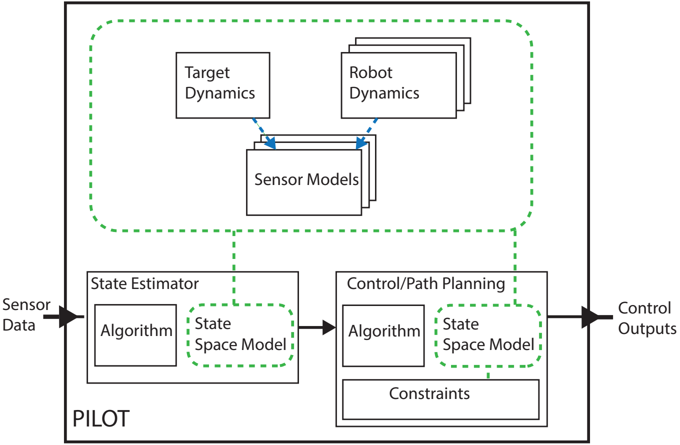
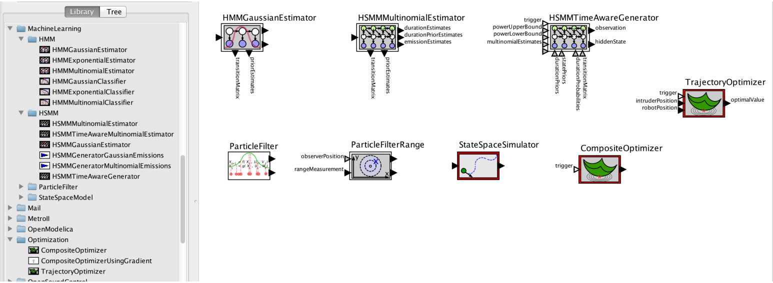


Figure : State-Space Aware System Architecture in PILOT

PILOT: Ptolemy Inference, Learning and Optimization Toolkit

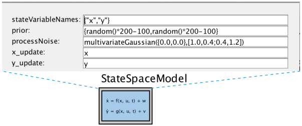
- Machine Learning
  - Bayesian parameter estimation, decoding and classification (Hidden Markov, Hidden Semi-Markov and Gaussian Mixture Models)
- Particle Filters
- Optimization (Convex Optimization and Gradient Descent)



State-Space Modeling in PILOT

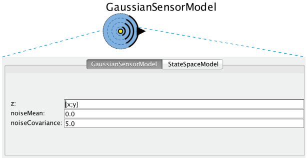
A general Bayesian state-space model is given by

$$
\begin{aligned}
x_0 &\sim \pi_X(x_0) && \text{(prior)} \\
\mathbf{z_t} | x_t &\sim g(x_t, u_t, t) && \text{(measurement model)} \\
x_{t+1} | x_t &\sim f(x_t, u_t, t) && \text{(state dynamics)}
\end{aligned}
$$



Example:

$$
\begin{aligned}
X_t &= \left[x_t ; y_t \right] \\
x_0, y_0 &\sim Uniform(-100, 100) \\
X_{t+1} &= X_t + \eta_t \\
z_t &= \sqrt{x_t^2 + y_t^2} + \omega_t
\end{aligned}
$$



$$
\begin{aligned}
&\omega_t \sim \mathcal{N}(0, \sigma_r^2) \\
&\eta_t \sim \mathcal{N}(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \Sigma)
\end{aligned}
$$

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Case Study: Cooperative RSN Control

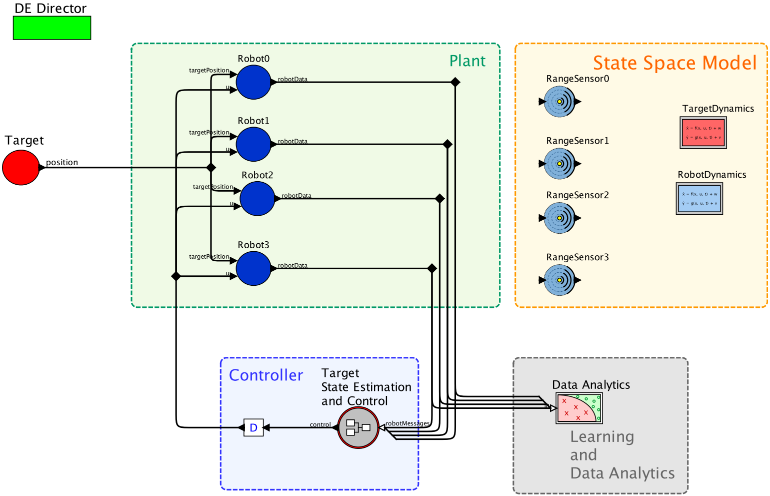


Figure : Top-Level Model for Range-Only Target Localization

Problem Definition

- A network of mobile sensor nodes
- Range-only sensors used to sense the position of mobile target(s)
- A cloud based application (centralized or decentralized) which takes range measurements and computes future robot trajectories to achieve a control goal
  - Localize target as fast as possible
  - Pursue the target
  - A multi-objective control goal
- Subject to environmental constraints
  - Obstacle/Collision avoidance
  - Speed and acceleration constraints

System Design for Mobile Robots in Ptolemy

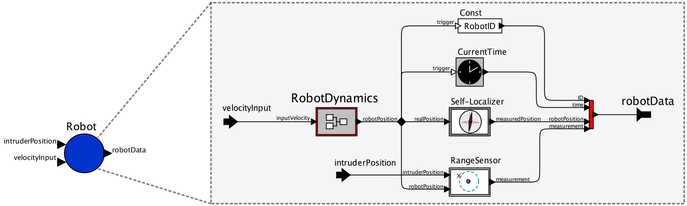
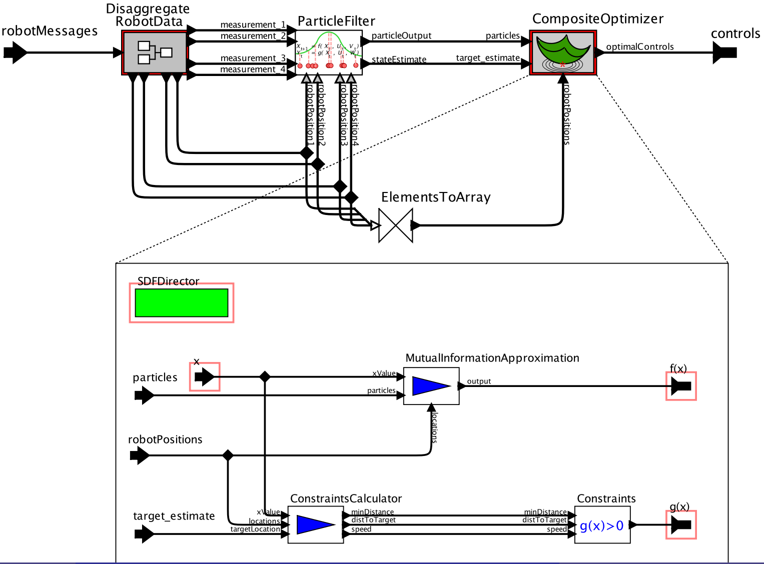


Figure : Model of a Robot Equipped with Range Sensor

- Heterogeneous models: Continuous and Discrete-Event
- Sensing an actuation can be simulated or
- the control logic can be integrated with the physical sensor network via `Accessors`

PILOT Control Workflow



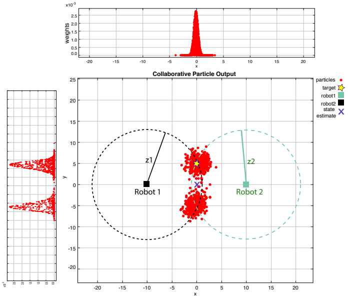
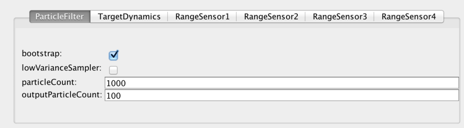


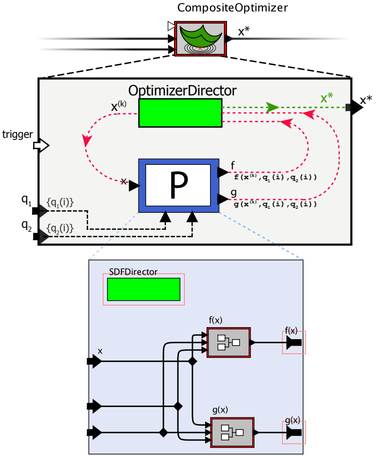
Figure : Sample particle output for state estimation using range-only sensing



CompositeOptimizer Workflow

$$\mathbf{x}^* = \underset{\mathbf{x}\in\mathbb{R}^n}{minimize}\ f(\mathbf{x}, q_1, q_2)$$

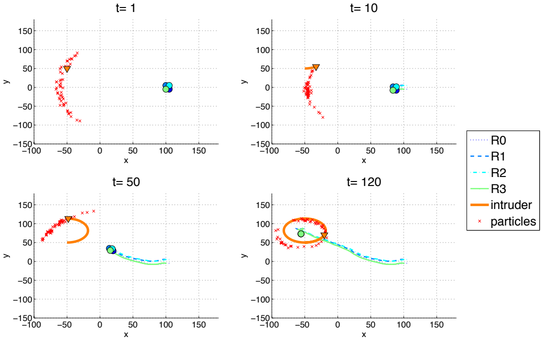
$$\text{subject to } g(\mathbf{x}, q_1, q_2) \geq 0\,,$$



Algorithm 1 `CompositeOptimizer`

Input: $\mathcal{Q} \Leftarrow \mathcal{Q}_i$
Output: $\mathbf{x}^*$ that is a local optimum of $f(\cdot)$
  define P: An actor that implements SDF, has inputs: $\mathbf{x}$, $\mathcal{Q}$ and outputs: f, g
  while $k < k_{MAX}$ &
      !CompositeOptimizer.converged() **do**
    $\mathbf{x}^{(k)} \Leftarrow$ OptimizerDirector.getNextX();
    P.readInputs($\mathbf{x} \Leftarrow \mathbf{x}^{(k)}$, $\mathcal{Q} \Leftarrow \mathcal{Q}_i$);
    P.execute();
    P.writeOutput($f(x^{(k)}, \mathcal{Q}_i) \Rightarrow f^{(k)}$, $g(x^{(k)}, \mathcal{Q}_i) \Rightarrow g^{(k)}$);
    OptimizerDirector.computeNextX($f^{(k)}$,$g^{(k)}$
  end while
  $\mathbf{x}^* \Leftarrow$ CompositeOptimizer.getOptimalX()

Experiments: Direct Pursuit



$$\mathbf{u_t}^* = \arg \min_{\mathbf{u}_t \in \mathcal{U}^M} ||\mathbf{R}_{t+1} - x_{t+1}||$$

$$\text{s.t}||u_t^{(i)}|| \leq V_{max}, \; i = 1, 2, ..., M$$

Experiments: MI Maximization

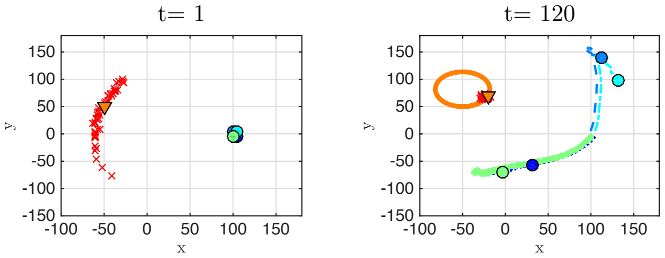


Figure : Sample trajectory for the MI Maximization Control Policy

$$\mathbf{u_t}^* = \arg\max_{\mathbf{u}_t \in \mathcal{U}^M} I(\mathbf{z}_{t+1}; x_{t+1})$$

$$\text{s.t} ||u_t^{(i)}|| \leq V_{max}, \; i = 1, 2, ..., M$$

Experiments: MI Maximization + Pursuit

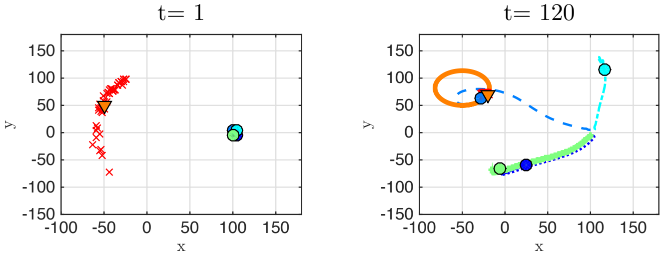


Figure : Sample trajectory for MI Maximization with Single Pursuer

$$
\mathbf{u}_t{}^{(i)*} = \begin{cases} \underset{\mathbf{u}_t{}^{(i)} \in \mathcal{U}}{\text{arg min}} \; \|\mathbf{R}_{t+1} - x_{t+1}\| & \\ \text{s.t} \|u_t^{(i)}\| \leq V_{max}, \;\; i = 1, 2, ..., M & \text{if } d_t{}^{(i)} < d_t{}^{(j)}, \; \forall j \neq i \\ & \\ \underset{\mathbf{u}_t{}^{(i)} \in \mathcal{U}}{\text{arg max}} \; I(z_{t+1}^{(i)}; x_{t+1}) & \\ \text{s.t} \|u_t^{(i)}\| \leq V_{max}, \;\; i = 1, 2, ..., M & \text{otherwise} \end{cases}
$$

$$
d_t{}^{(i)} := \|R_{it} - x_t\|, \;\; i \in \{1, 2, ..., M\}
$$

Dynamic Performance Evaluation

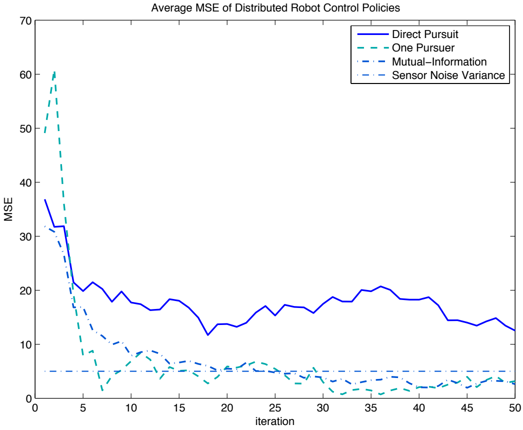


Figure : Comparison of Algorithmic Accuracy

Environmental Fault Modeling: Binary Erasure Channel

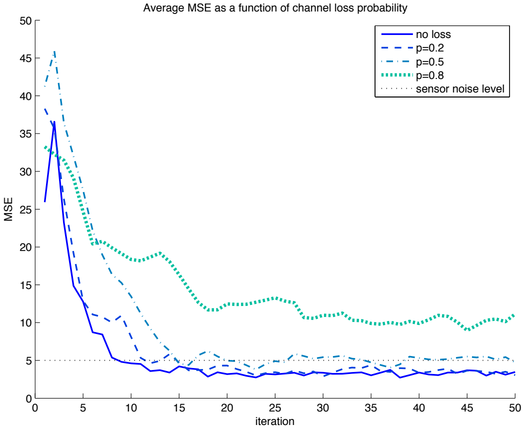


Figure : Comparison of Cooperative Localization Error with Probabilistic Channel Loss

Robotic Sensor Network Control

Work in Progress: Distributed Optimization Enabled by Vert.x (or ROS?)

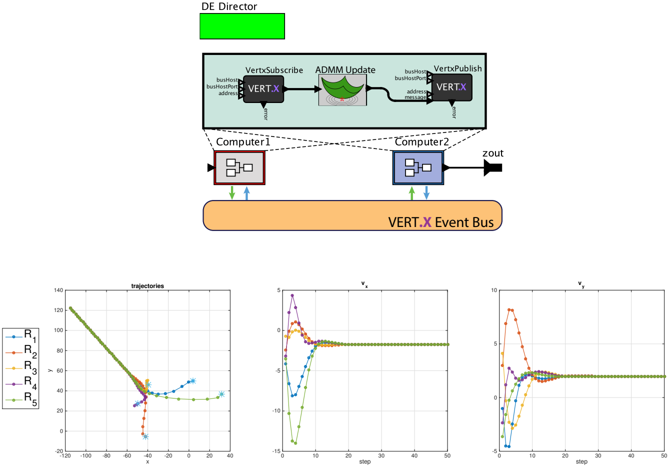


Figure : Model-predictive control of flocking robots on a ring network topology

Thanks!

- PILOT is shipped as part of the open-source Ptolemy II Project
- RSN control demos can be accessed online at:
- `http://ptolemy.eecs.berkeley.edu`