Energy-Based Visual SLAM for Outdoor Robotics

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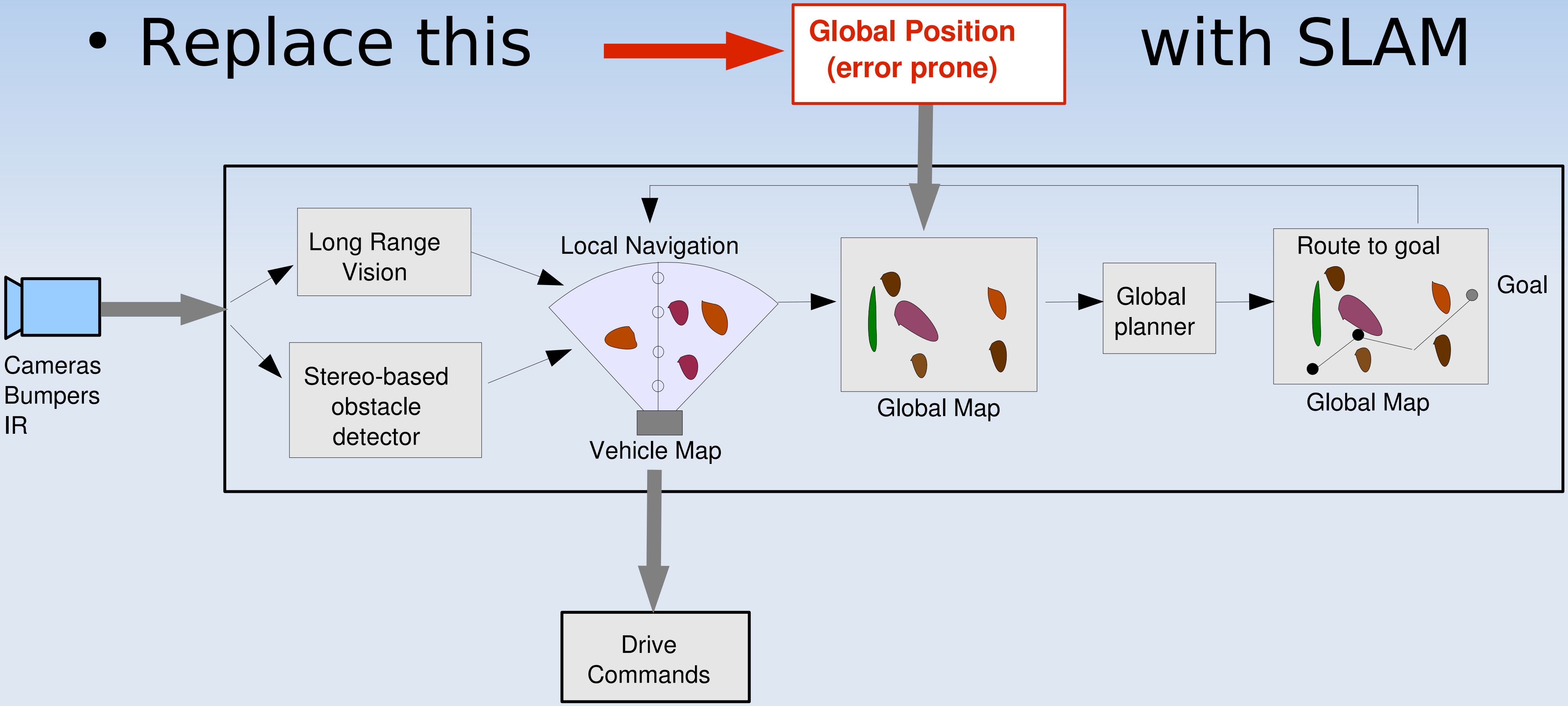
LAGR (Learning Applied to Ground Robotics)

- 9 teams, 9 flash drives, 1 robot
- Navigate through a novel course in natural terrain.
- Three time trials, with memory retained between trials.
- Goal: beat baseline system's time by a factor of 3.

My part

- Replace this  with SLAM

Localization (the L in SLAM)

- Given a map, determine the robot's location from observations.
- Example use: museum tour guide robot
- Picture: RHINO, from “Experiences with an Interactive Museum Tour-Guide Robot”, Wolfram Burgard et al

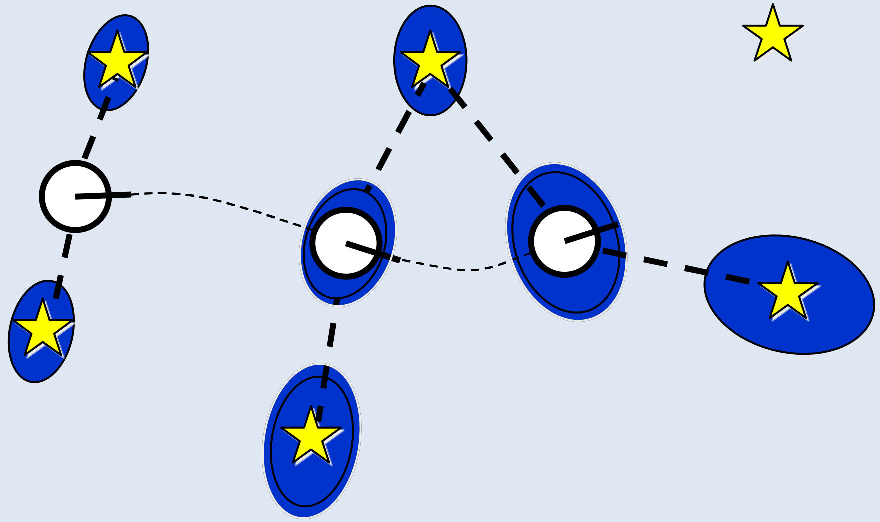
Mapping (the M in SLAM)

- Given the robot's location, create a map from observations.
- Example: Generating maps for localization, because blueprints are inaccurate.

Hans Moravec 2002, http://www.ri.cmu.edu/~hpm/project.archive/robot.papers/2002/ARPA.MARS/Report.0202.html

SLAM

- Simultaneous Localization and Mapping
- Given observations, simultaneously generate a map and localize the robot within it.



Picture from slam.ppt at www.probabilistic-robotics.org

Outline

- SLAM:
  - Classical Kalman Filter-based approach
  - Energy-based SLAM
- Visual Odometry:
  - Current methods
  - Cheaper approaches used in conjunction with SLAM

Classical SLAM (EKF)

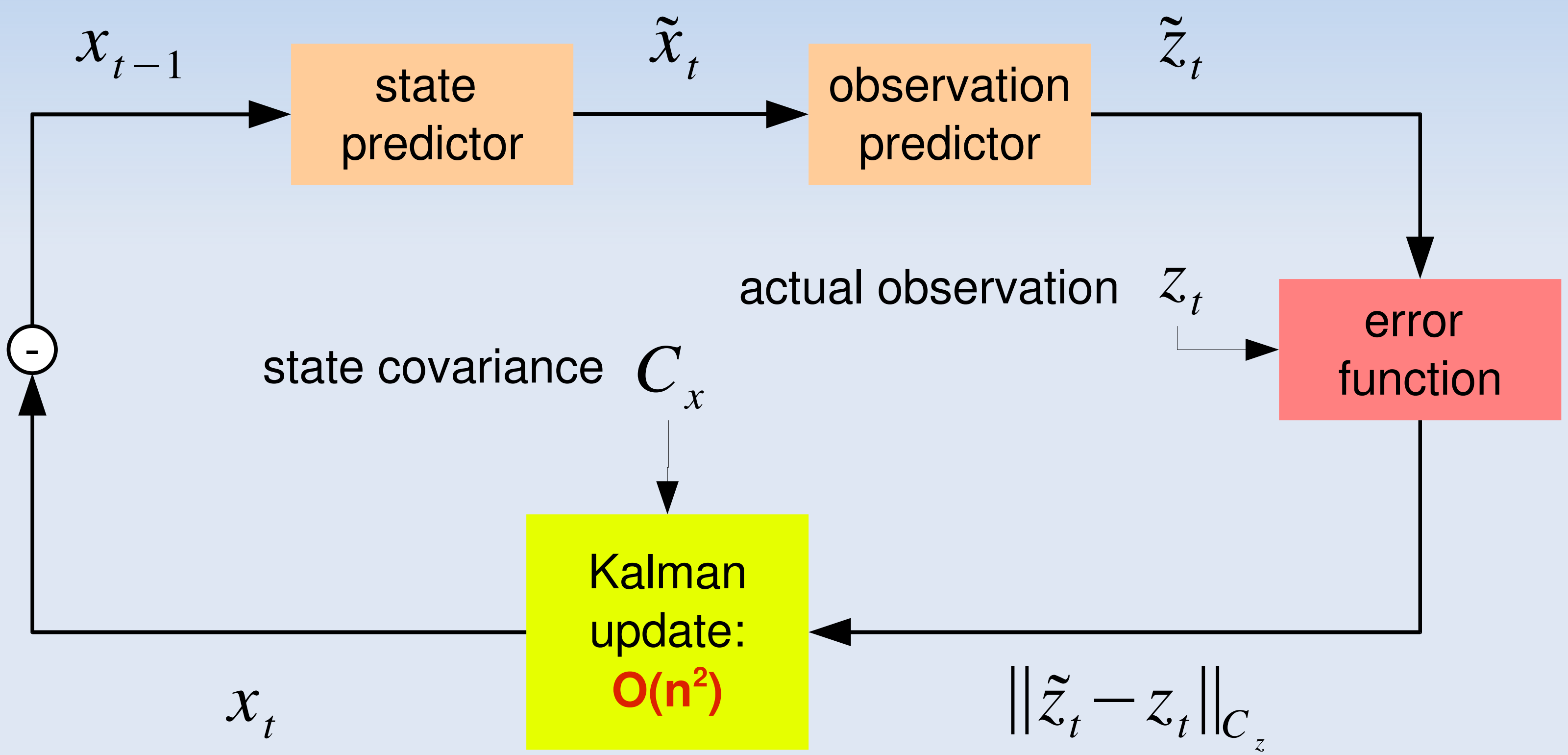
- Estimate hidden online state and its covariance using an Extended Kalman Filter.

$$\vec{x} = [r_x, r_y, r_\theta, m_x^1, m_y^1, \ldots, m_x^n, m_y^n]$$

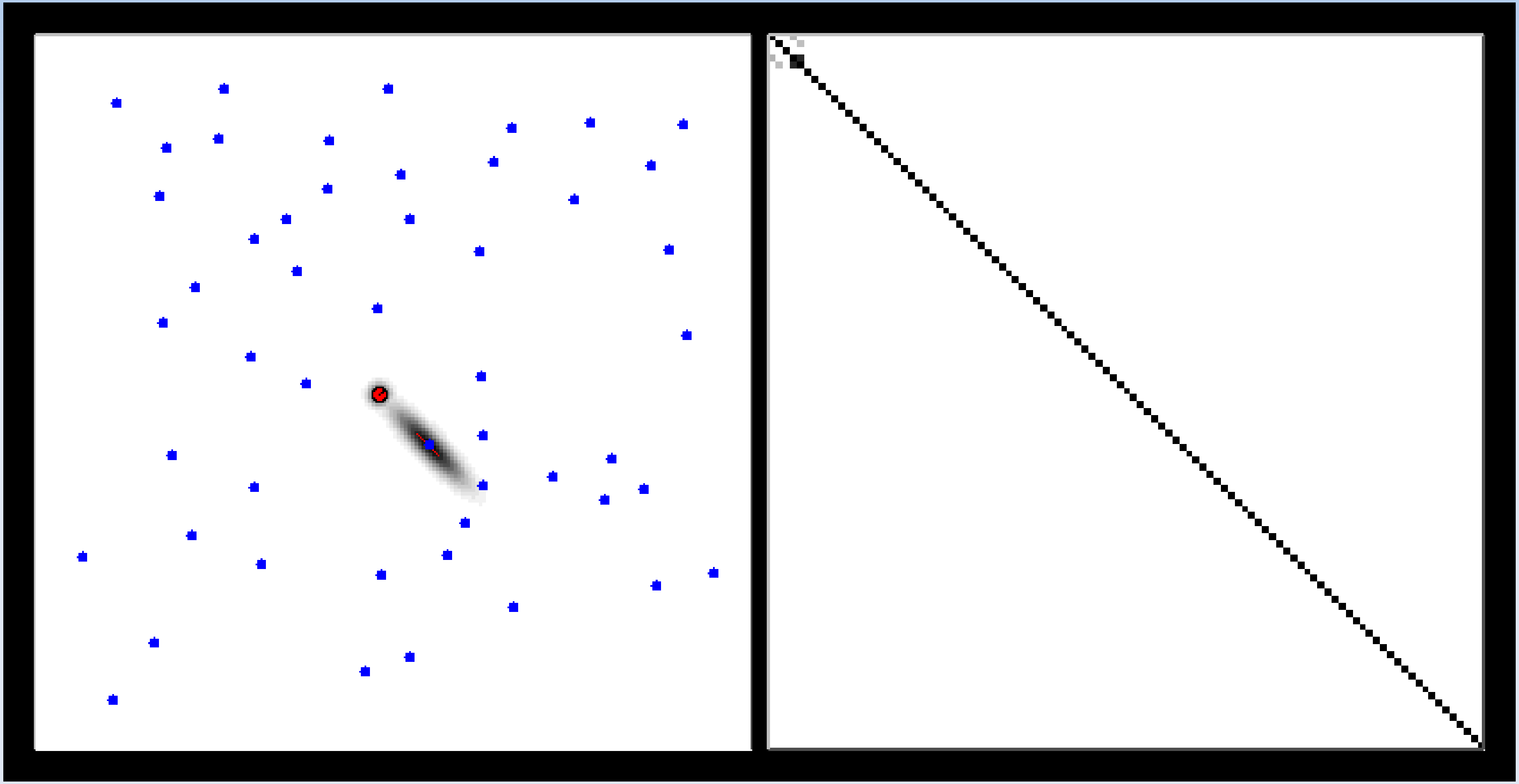
- Observations = sensor input
  - For example, pixel coordinates of landmarks.

$$\vec{z} = [z_x^1, z_y^1, \ldots, z_x^n, z_y^n]$$

Classical EKF SLAM

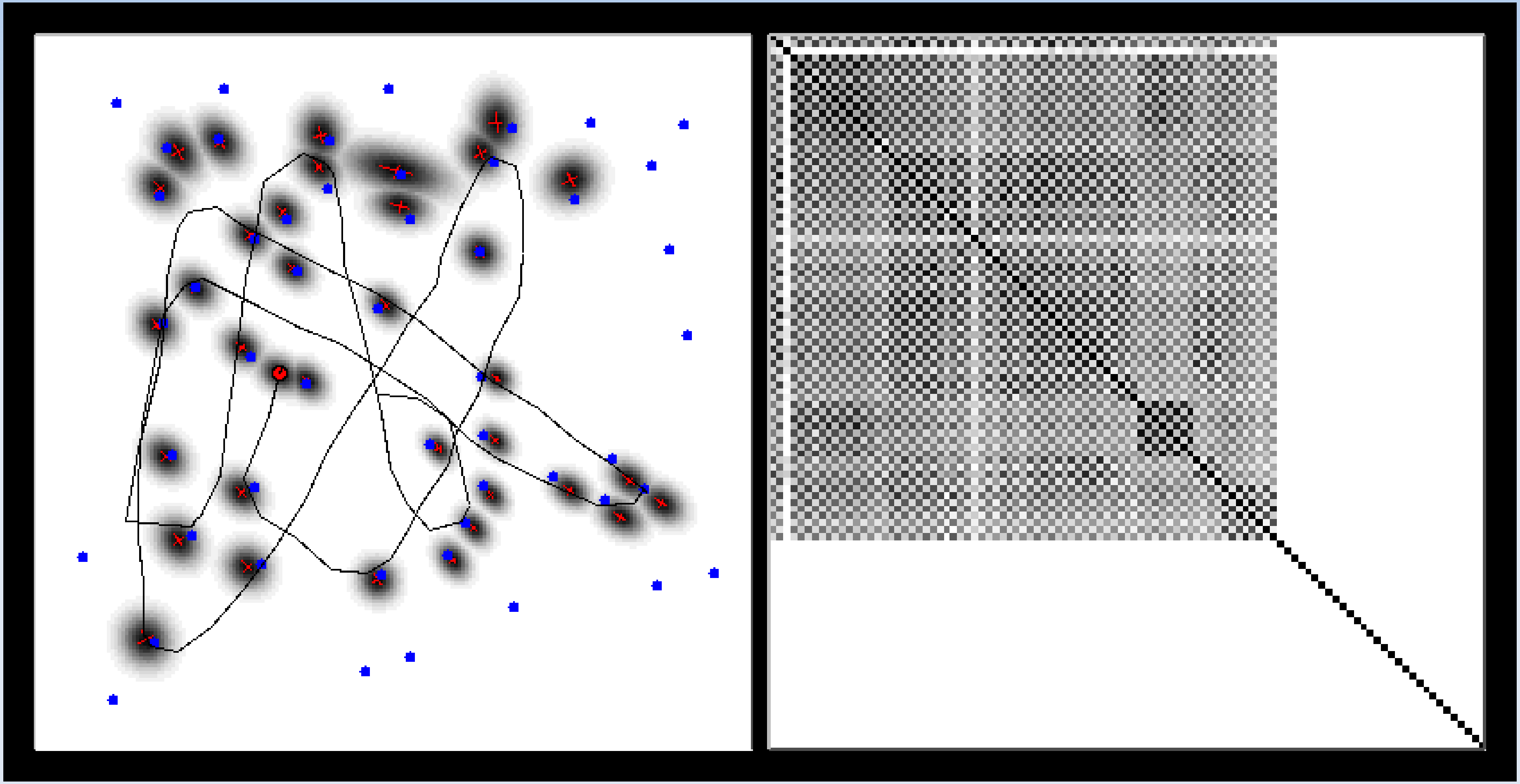


Classical EKF SLAM



From “slam.ppt” on www.probabilistic-robotics.org

Classical EKF SLAM



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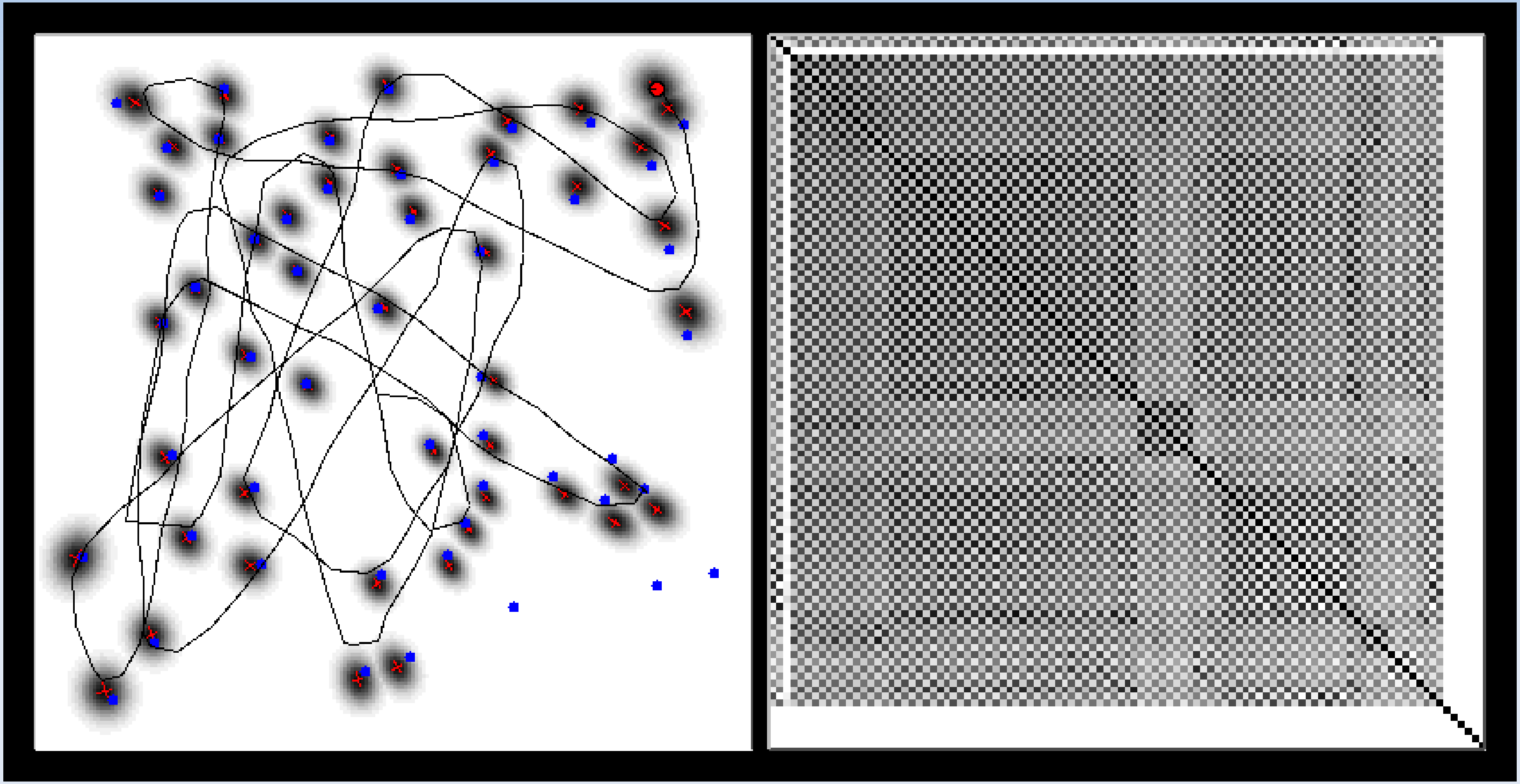
Classical EKF SLAM



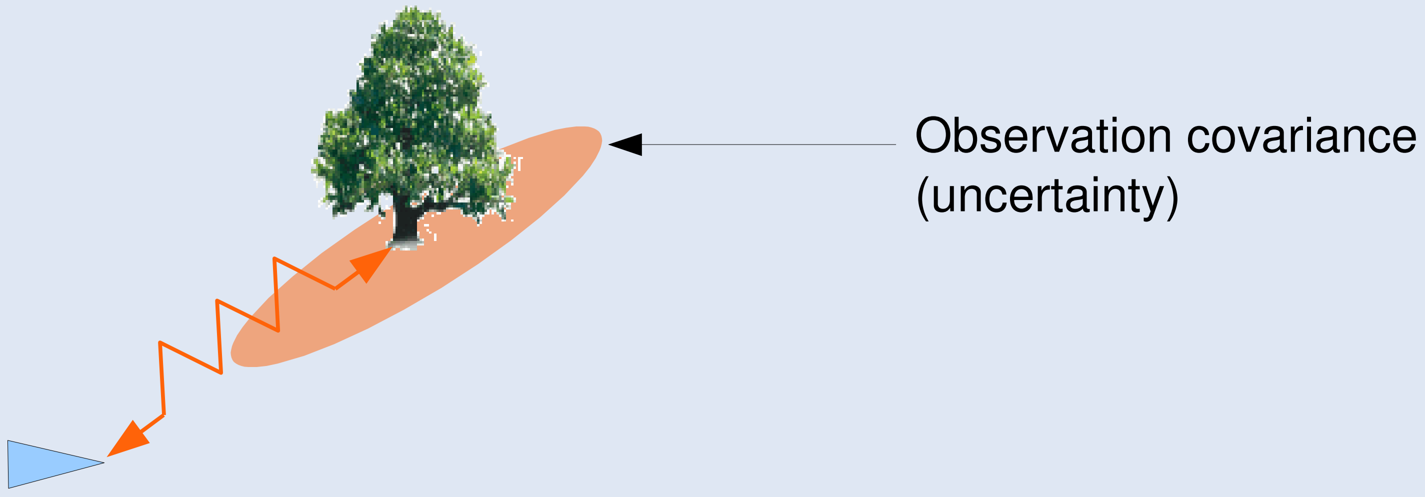
From “slam.ppt” on www.probabilistic-robotics.org

Classical EKF SLAM

- There are more landmarks other sensor inputs than there are poses.
- EKF:
  - $O(n^2)$ in storage.
  - $O(n^2)$ in processing **each time we move**.
  - Linearizes process and observation models.

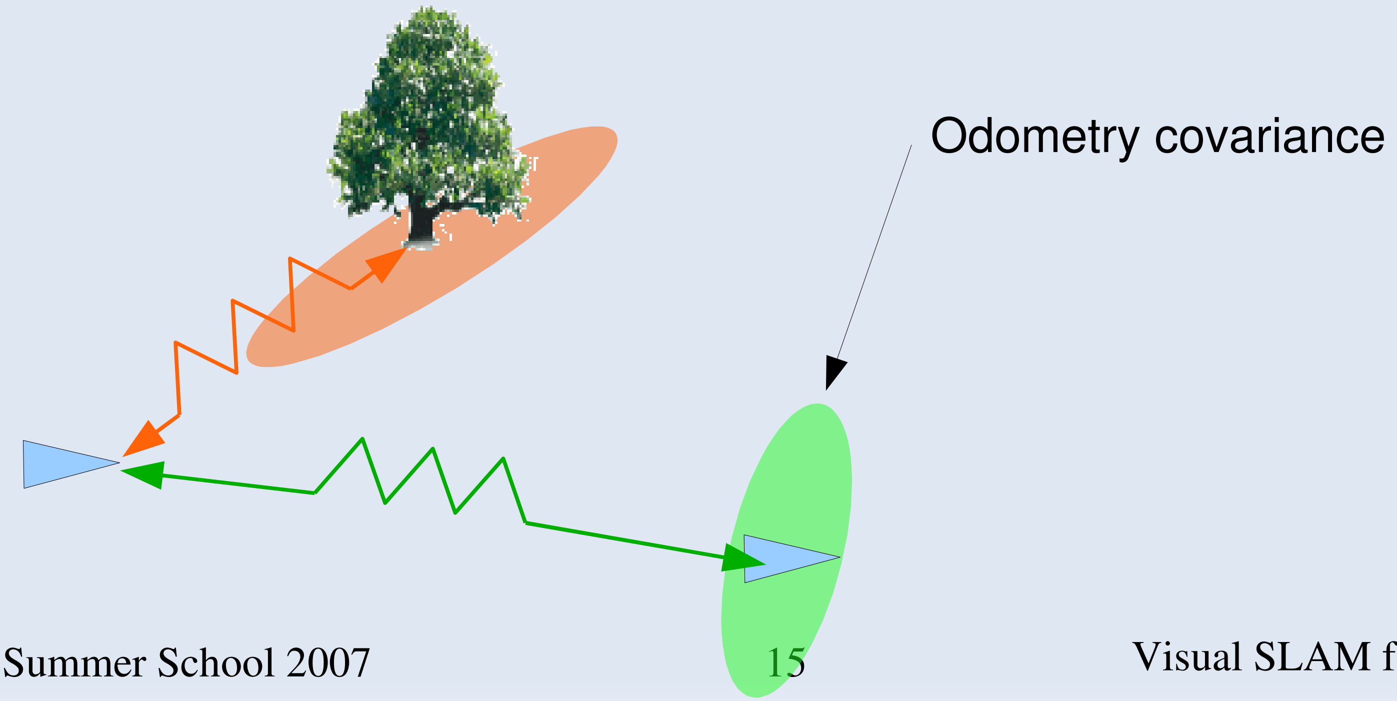
Graph SLAM

- An observation is a soft constraint between one robot pose and one landmark



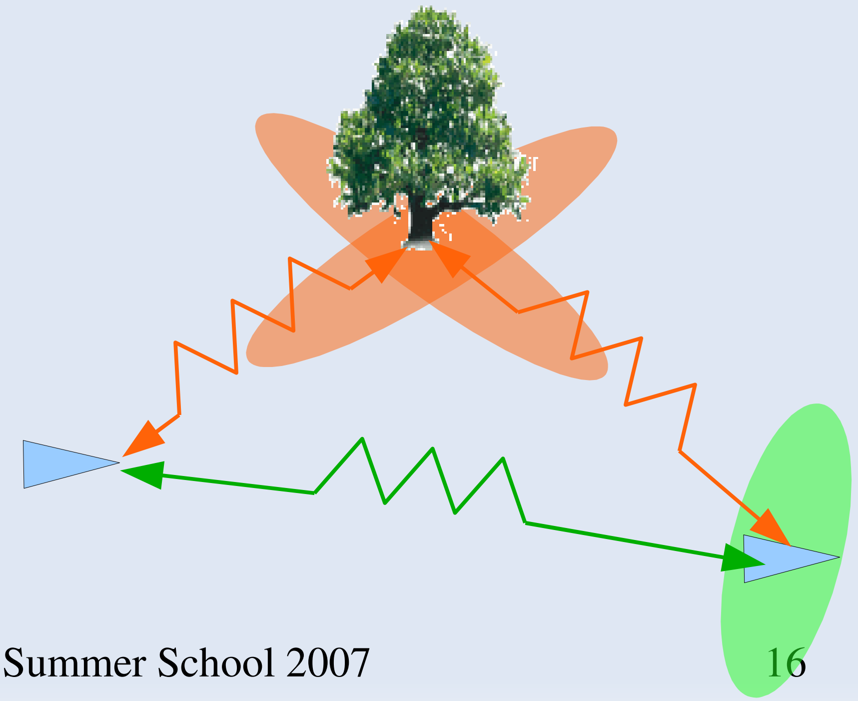
Graph SLAM

- Odometry gives a soft constraint between successive poses.



Graph SLAM

- If you retain past robot poses, you can build up a graph.



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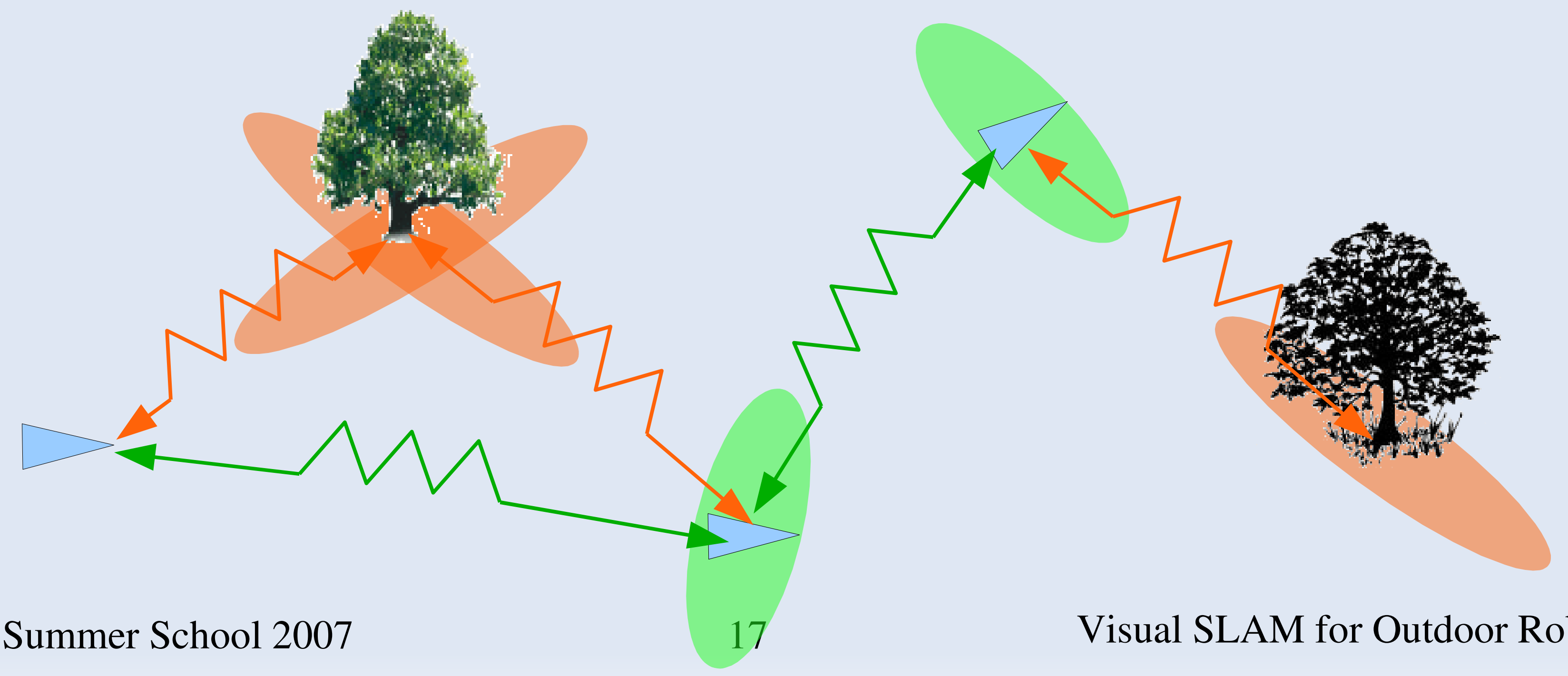

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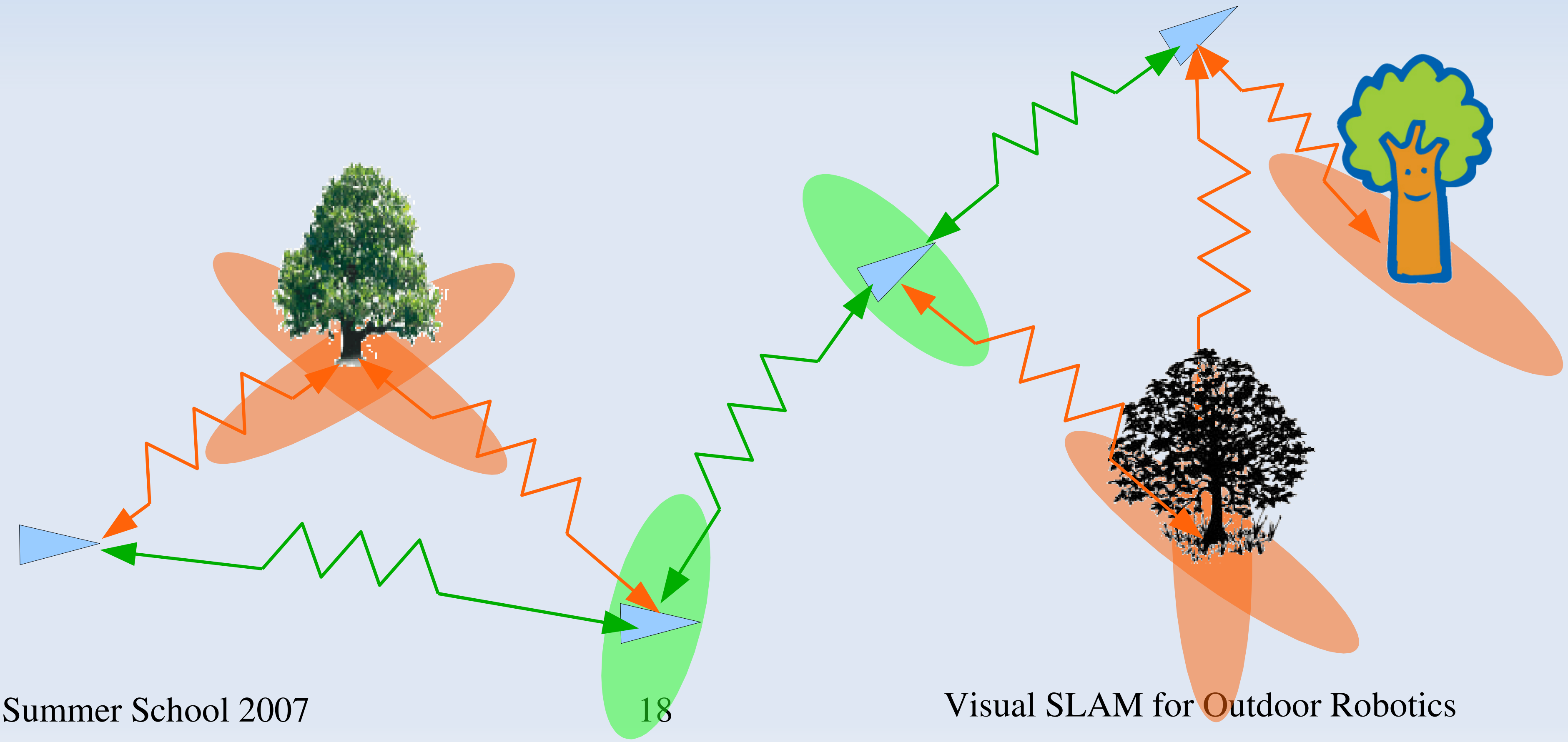
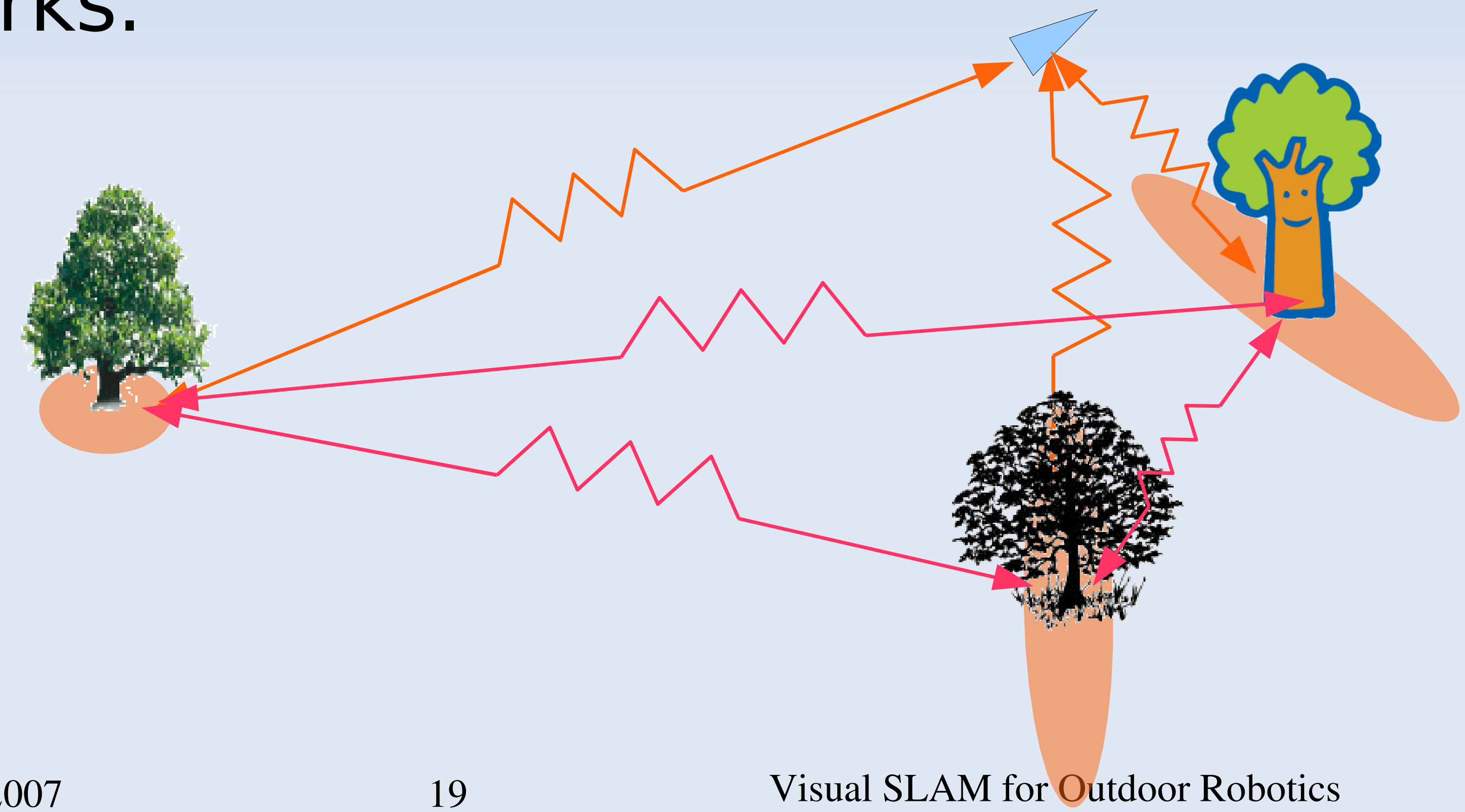


Graph SLAM

- EKF marginalized out past poses, and built a fully connected graph of landmarks.



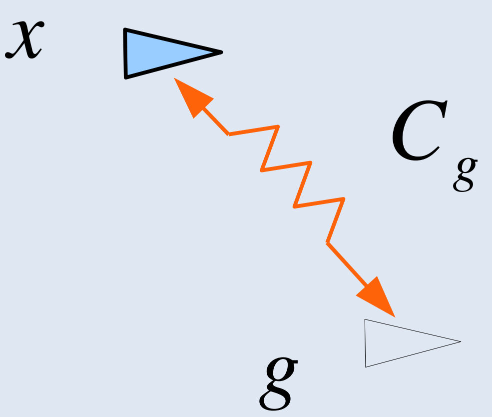
Graph SLAM

- Formulates SLAM as optimizing an energy function of soft constraints.
- Full nonlinear optimization is slow, offline.
- Use stochastic updates instead.

Energy function

- Energy function: a sum of independent differentiable sub-energy modules.
- For example, the GPS energy:

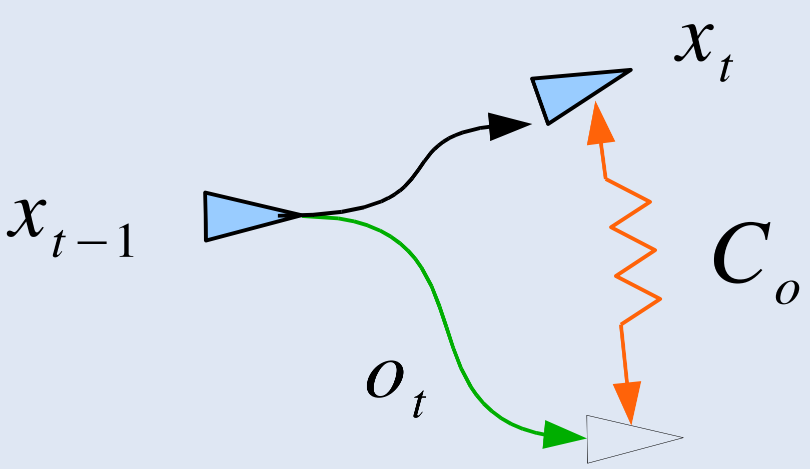
$$E_g(x_t, g_t) = \|g_t - x_t\|_{C_g}$$



Energy function

- The odometry energy:

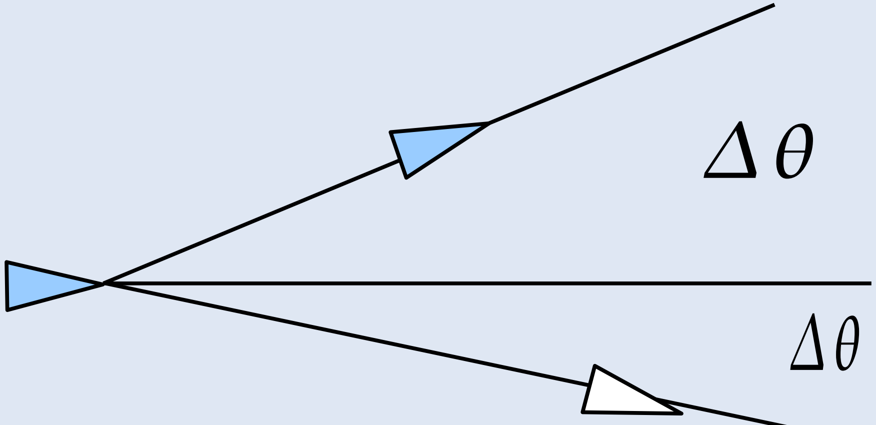
$$E_g(x_t, x_{t-1}, o_t) = \|\Delta x_t - o_t\|_{C_o}$$



Energy function

- The visual compassing energy:

$$E_v(\theta_t, \theta_{t-1}, \phi_t) = \|\Delta\theta_t - \phi_t\|_{C_v}$$



Energy function

- The total energy:

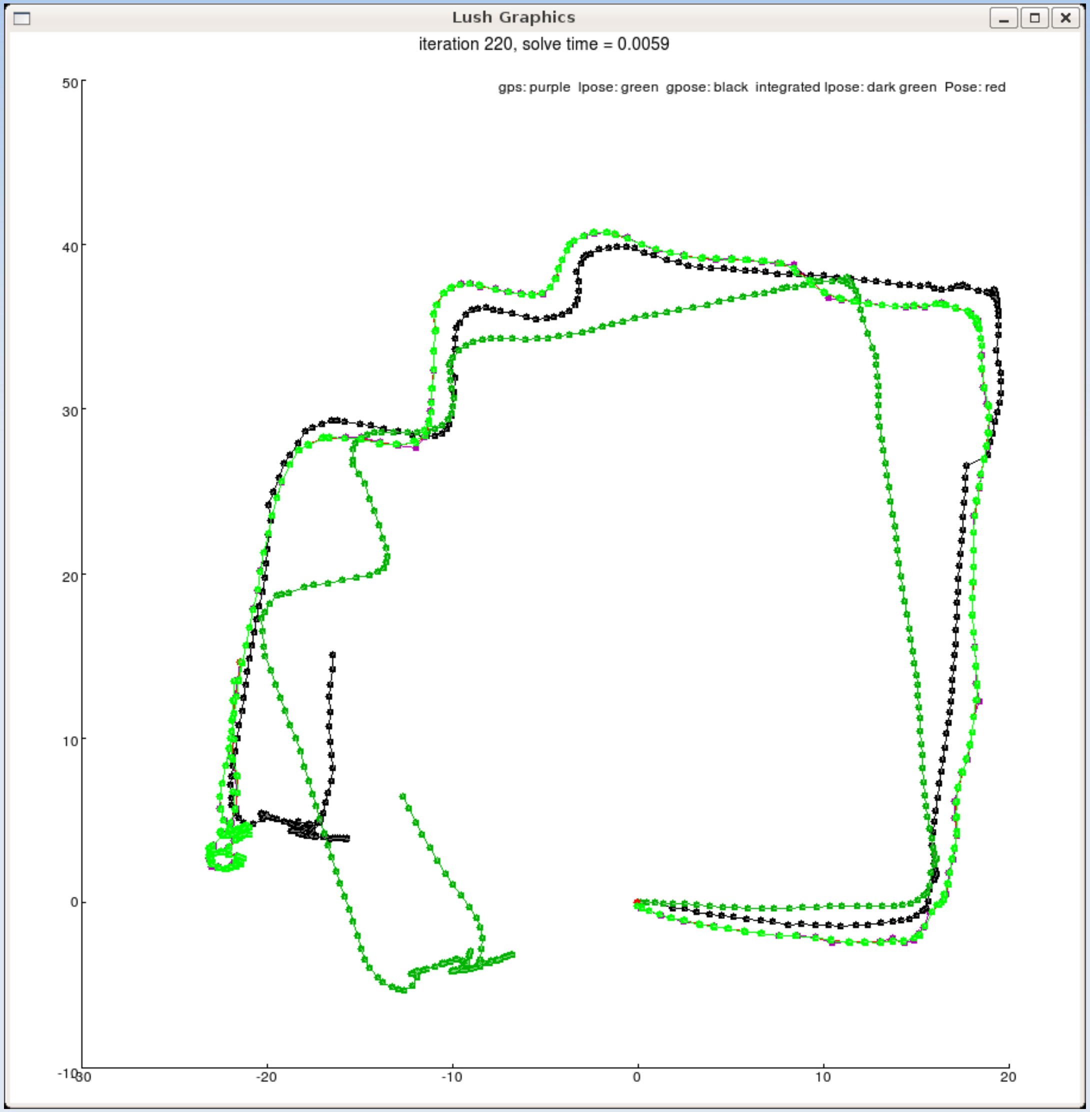
$$E = \sum_{t \in T} E_g + E_o + E_v \quad [+ \;\cdots]$$

- At each timestep,
  - Select a set T of poses to optimize.
  - Accumulate energy gradients into them and any landmarks they affect.
  - Gradient descent with diagonal Hessian.

Results: visual compassing

- Show movie

Results: Overcoming wheel slip



Future work

- Landmarks
  - Use Hessian uncertainty windows for efficient landmark search.
- Visual odometry
  - Use ground plane patches for translation information.
- Learning sensor uncertainty
  - Hold poses constant, optimize w.r.t. sensor covariance parameters.