



FastSLAM: Outdoor Implementation with Known and Unknown Data Association

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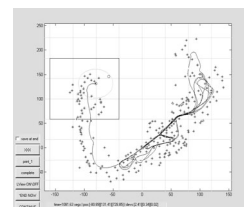
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SLAM in Large Environments :

- **CEKF**
 - Solve the problem for high frequency sensors in local areas
- **Decorrelation Techniques**
 - Address the problem of full update and memory requirements
- **Cluttered Environments:**
 - Data association will be a continuous problem



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- **Probabilistic Motion Model** $p(x_t / u_t, x_{t-1})$
- **Measurement Model** $p(z_t / x_t, \theta, n_t)$
- **SLAM Problem** $p(x^t, \theta / z^t, u^t) \quad \text{time: } 1..t$
- **If the path of the robot is known then all individual landmarks estimation problems are independent**

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FastSLAM

- **Decomposes the SLAM problem into a localization problem and a number of landmark estimation problems conditioned on the robot pose estimate**
 - Uses a particle filter to estimate the posteriori over the robot paths.
 - Each Particle possesses k Kalman filters that estimate the k landmarks location conditioned on the path estimate.
 - The computational requirement will be $O(M*k)$ with M and k the number of particles and landmarks respectively

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- The slam Problem can be decomposed into

K+1 estimation problems:

- Posteriori over the robot path
- K problems estimating the location of the landmarks

$$p(x^t, \theta / z^t, u^t) = p(x^t / z^t, u^t) \prod_k p(\theta_k / x^t, z^t, u^t)$$

- The Robot path estimation is implemented with a particle filter
- The landmark positions are estimated with Kalman Filters

$$p(x^t / z^t, u^t)$$

$$p(\theta_k / x^t, z^t, u^t)$$

- The full posteriori of path and landmark is represented by the following sample set

$$X_t = \{x^{t,[m]}, \bar{\theta}_1^{[m]}, P_{\theta_1}^{[m]}, \dots, \bar{\theta}_K^{[m]}, P_{\theta_K}^{[m]}\}$$

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Known Data Association

- The Experimental results are done with real data
- It is not possible to “measure” correspondence (Data association)
- The data association was implemented by a KF based SLAM
 - Landmarks were extracted
 - Once accepted, they were included in a list with appropriate time stamp
 - This list has the observations used by FastSLAM

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Known Data association

Experimental Runs

- **Car Park**
 - Beacon consisted of 60 mm steel poles
 - Clearly defined and easily extracted from the environment
 - Accurate Determination of landmark Position

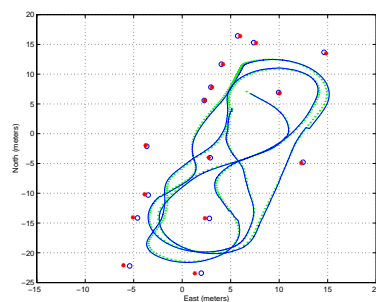


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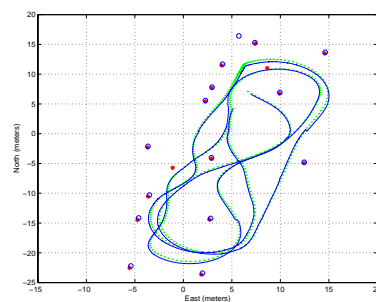


EKF and FastSLAM Map and Trajectory



EKF SLAM

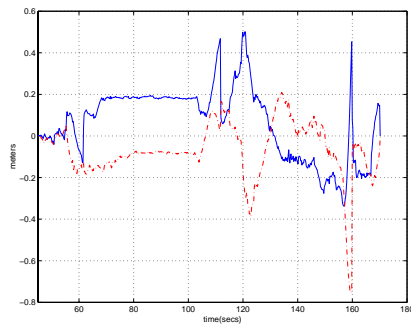
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FastSLAM

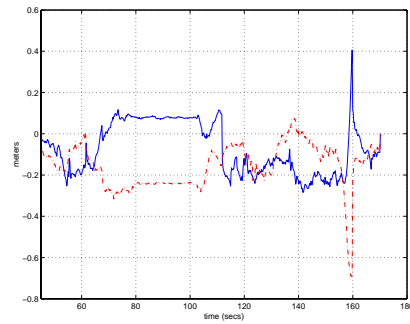
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EKF and FastSLAM absolute Error



EKF SLAM

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Known Data association

Experimental Run:

- **Victoria park**
 - Large Environment
 - Different type of landmark
 - Larger errors in landmark position determination

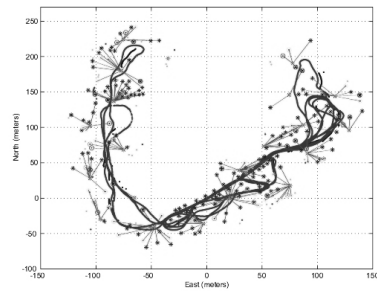


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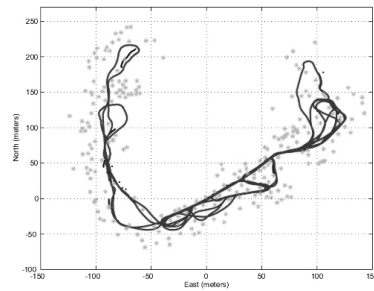


Known Data Association



EKF SLAM

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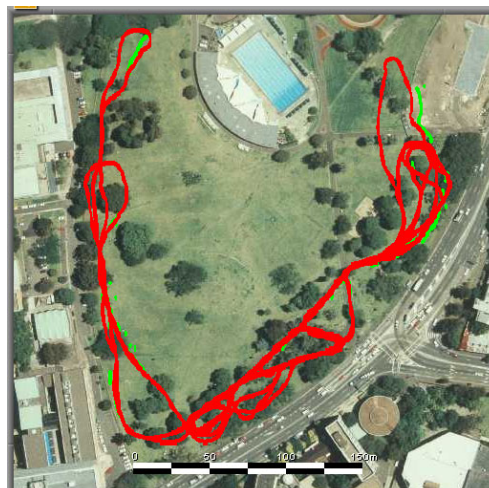


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FastSLAM: Victoria Park



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Unknown Data Association

Data Association Problem:

- Associating the observation to the correct state
- Initializing new tracks
- Detecting and rejecting spurious measurements

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$$Beacon = \min (innov \cdot S^{-1} \cdot innov^T + \ln(|S|))$$



Unknown Data Association

Principle of Data Association

- Innovations sequence

$$v_{ij}(k) = z_i(k) - \hat{z}_j(k)$$

- Normalised Innovations sequence

$$d_{ij}^2(k) = v_{ij}^T(k) S_{ij}^{-1}(k) v_{ij}(k)$$

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$$p(\mathbf{z}_t | \mathbf{z}_{1:t-1}, \mathbf{x}_{1:t-1}) = p(\mathbf{z}_t | \mathbf{x}_{1:t-1})$$



Unknown Data Association

- **Gate Validation:** Associate only if there is one possible hypothesis
- **Nearest Neighbour:** Select the “nearest” state to the observation
- **Multi Hypothesis Tracking:** Use all the possible hypothesis

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Unknown Data Association

Multi Hypothesis Tracking

- **EKF Slam:**
 1. Run a new filter in parallel
 2. Pruning Techniques
- **FastSlam**
 1. Create a new particle
 2. Resampling

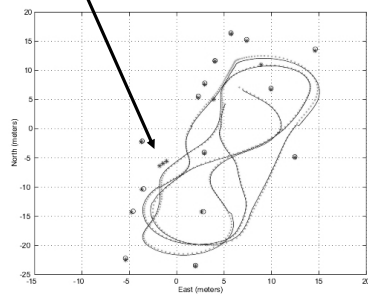
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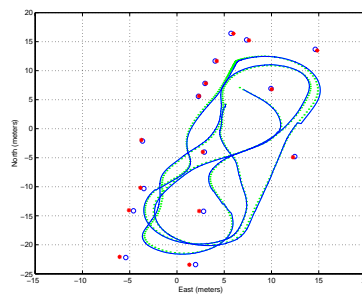
Experimental Results Car Park

Additional Landmarks



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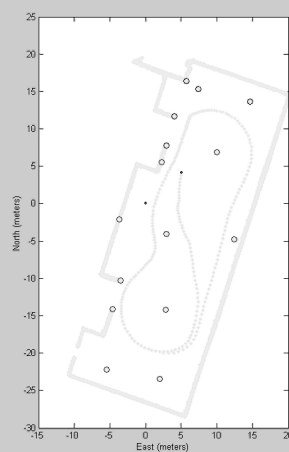


EKF SLAM

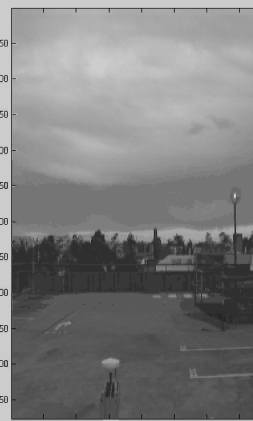
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Experimental Results Car Park



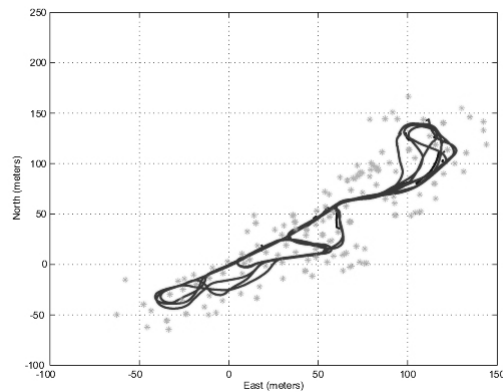
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Experimental Results Victoria Park



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Current Research

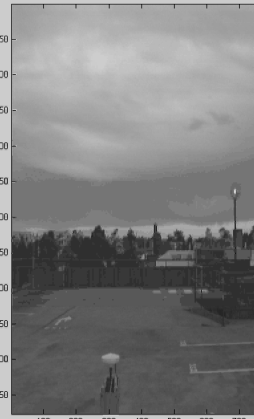
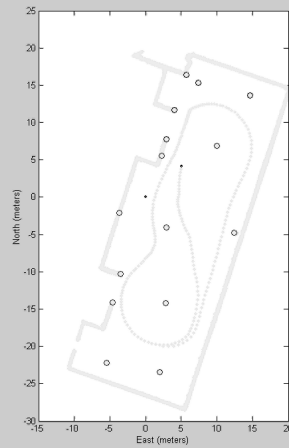
- **Data Association**
 - Multiple Hypothesis
 - $H1-n$: All Possible Existing Landmarks
 - H_0 : Spurious measurement
 - H_n : New object
 - Control of number of Particles
- **Addressing the covariance reduction Problem**
- **Consistency**
- **Extension to larger systems**

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Experimental Results Car Park



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