New Concepts in Robotic Mapping: PHD Filter SLAM

Martin Adams
Dept. Electrical Engineering, CMRSP, AMTC
University of Chile (martin@ing.uchile.cl)

Planning, Perception and Navigation for Intelligent Vehicles, IROS 2013
1. What’s in a Measurement:
   - Landmark Existence and Spatial Uncertainty
   - Why Radar?

2. Simultaneous Localisation & Map Building (SLAM).
   - PHD SLAM – Implementation.

3. Comparison of Vector Based SLAM (MH–FastSLAM) and PHD–SLAM – Results.
Sensing the Environment

Clearpath Robotic Skid Steer Platform

- Acumine Radar 360 deg. scanning unit, 94GHz FMCW
- Sick LD–LRS1000 Scanning LRF
- Microsoft Kinect camera system
What’s in a Measurement?

(a) A–Scope display at chosen radar bearing angle

(b) Detection theory applied to A–Scope from (a)

Robotic Interpretation:

(c) Spatial Interpretation

Area under dist. = 1

Result: Detection decision at range $r_k^i$

A-priori range uncertainty assumed/known $(\sigma_k^2)^i$

Subtly assumes unity detection probability $P_{D} = 1$

Radar Interpretation:

(e) Detection Information

Multiple detection hypotheses $H_1(r(q))$

Associated probabilities of detection $P_D$

Associated probability of false alarm $P_{fa}$

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What’s in a Measurement?

• In reality – Probability of Detection less than unity, but may not be known.

• However, landmark/feature measurements in SLAM result from a feature detection algorithm.

• Principled algorithms provide estimates of $P_D$ and $P_{fa}$, or they can be estimated a-priori (e.g. RANSAC).

• Ideal scenario: Represent all detection hypotheses in terms of their:

$$r^i_k, \left(\sigma^2_k\right)^i, P_D(r^i_k) \text{ and } P_{fa}$$

(i.e. range, spatial uncertainty, detection uncertainty and false alarm probability).
Radar Based Projects: A*Star – Radar vs. Ladar

✓ Wider beam width
✓ Foliage penetration
Q: Why do we even care about error in the number of landmarks?

A: Catastrophic consequences in applications such as search & rescue, obstacle avoidance, UAV mission...
Importance of $P_{fa}$ – False Alarms

Radar detections registered to ground truth location.
Radar Based Projects: A*Star – Radar vs. Ladar

Video: Raw_Data_Display.avi
Presentation Outline

1. What’s in a Measurement:
   - Landmark Existence and Spatial Uncertainty
   - Why Radar?

2. Simultaneous Localisation & Map Building (SLAM).
   - PHD SLAM – Implementation.

3. Comparison of Vector Based SLAM (MH–FastSLAM) and PHD–SLAM – Results.
SLAM Fundamentals

• In an unknown environment – robot & feature positions must be estimated simultaneously – SLAM.

• SLAM is a probabilistic algorithm

\[ p(x_t, m \mid z_{1:t}, u_{1:t}) \]

\[ x_t = \text{State of the robot at time } t \]

\[ m = \text{Map of the environment} \]

\[ z_{1:t} = \text{Sensor inputs from time 1 to } t \]

\[ u_{1:t} = \text{Control inputs from time 1 to } t \]

• Update distribution estimate with Bayes theorem.
SLAM: Approximate Particle Solutions – FastSLAM

A Factorised Solution to SLAM (FastSLAM):

Define joint vehicle \textit{trajectory} \& map vector state: \( \zeta_{0:k} = [X_{0:k}, M_k] \)

The posterior distribution on this modified, joint state could then be factorized as,

\[
p_k|_k(\zeta_{0:k}|Z_{0:k}, U_{0:k-1}, X_0) = \prod_{l=1}^{m} p_k|_k(X_{0:k}|Z_{0:k}, U_{0:k-1}, X_0),
\]

Particles represent trajectory distribution:

\[
p_k|_k(X_{0:k}|Z_{0:k}, U_{0:k-1}, X_0) \approx \sum_{i=1}^{N} w_k^{(i)} \delta(X_{0:k} - \hat{X}_{0:k|k}^{(i)}).
\]

each with their own EKF map estimate.
SLAM: Approximate Particle Solutions – FastSLAM

Finding the particle weights:

Each particle receives weight related to how well the measurements (sensor scan), recorded from the true pose, when superimposed onto each particle, match the expected measurements.

This is: \[ w_k^{(i)} \propto g_k \left( Z_k \mid X_{0:k}, Z_{0:k-1} \right) \]

Requires usual (fragile) feature association and management routines.

Particle resampling then takes place, based on the particle weights.
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Particle resampling then takes place, based on the particle weights.

Highest weight particle chosen as estimated trajectory & its map as estimated map (MAP estimate).
SLAM: Multi-Hypothesis (MH) FastSLAM

Multi-Hypothesis FastSLAM:

For each trajectory particle, multiple feature to detection associations are possible.
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Multi-Hypothesis FastSLAM:

For each trajectory particle, multiple feature to detection associations are possible.

For each possible association, an intermediate particle is defined.

For each of these particles, the measurement likelihoods are Calculated, and a corresponding weight determined.
SLAM: Multi-Hypothesis (MH) FastSLAM

Ground-truth robot and feature positions & single particle representation:
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Record sensor scan (range, bearing) – from ACTUAL pose.
SLAM: Multi-Hypothesis (MH) FastSLAM

Superimpose recorded scan onto particle.
SLAM: Multi-Hypothesis (MH) FastSLAM

Move robot via computer input steering and velocity commands.
SLAM: Multi-Hypothesis (MH) FastSLAM

Apply motion model and sampled noise to particle.
SLAM: Multi-Hypothesis (MH) FastSLAM

Predict new measurements.
SLAM: Multi-Hypothesis (MH) FastSLAM

Record new scan (range, bearing) – From ACTUAL new pose.
SLAM: Multi-Hypothesis (MH) FastSLAM

Superimpose new scan onto new particle pose.
SLAM: Multi-Hypothesis (MH) FastSLAM

Generate new particle, at same pose, which carries data association possibility 1.
Generate new particle, at same pose, which carries data association possibility 2.
SLAM: Multi–Hypothesis (MH) FastSLAM

Generate new particle, at same pose, which carries data association possibility 3.
SLAM: Multi-Hypothesis (MH) FastSLAM

Generate new particle, at same pose, which carries false alarm possibility.
SLAM: Multi-Hypothesis (MH) FastSLAM

Generate new particle, at same pose, which carries New feature possibility.
SLAM: Multi-Hypothesis (MH) FastSLAM

Multi-Hypothesis FastSLAM:

For each trajectory particle, multiple feature to detection associations are possible.

For each possible association, an intermediate particle is defined.

For each of these particles, the measurement likelihoods are calculated, and a corresponding weight determined.

Resampling, based on the weights is carried out, yielding the same initial particle number.
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A general vector based SLAM method, allowing MH feature Association.
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A general vector based SLAM method, allowing MH feature association.

However, not clear how to include detection probabilities, and MH tracking has not been proved Bayes optimal.
A Random Finite Set (RFS) Approach [Mullane, Vo, Adams ‘09]

Given $X^1$:
$M = [m_1, m_2, m_3, m_4, m_5, m_6, m_7]$

Given $X^2$:
$M = [m_4, m_3, m_2, m_1, m_5, m_7, m_6]$

Given $X^3$:
$M = [m_6, m_7, m_5, m_4, m_3, m_2, m_1]$

- Estimated map vector depends on vehicle trajectory?

- RFS makes more sense as order of features cannot/should not be significant [Mullane, Adams 2009].
A Random Finite Set (RFS) Approach

Untangle:

\[ Z = [z_1, z_2, z_3, z_4, z_5, z_6, z_7] \]

\[ M = [m_1, m_2, m_3, m_4, m_5, m_6, m_7] \]
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Current vector formulations require data association (DA) prior to Bayesian update:

Why? Features & measurements rigidly ordered in vector-valued map state.

RFS approach does not require DA.

Why? Features & measurements are finite valued sets. No distinct order assumed.
A Random Finite Set (RFS) Approach

How to relate measurements and states of different dimensions?
What is a RFS Measurement?

\[ Z = \{z^1, \ldots, z^3\} = \{[r^1 \theta^1]^T, \ldots, [r^3 \theta^3]^T\} \] (1)

Hence, at any instant, a sensor can be considered to collect a finite set \( Z = \{z^1, \ldots, z^3\} \) of measurements \( z^1, \ldots, z^3 \) from a measurement space \( Z_0 \) as follows:

\[
\begin{align*}
Z &= \emptyset \quad \text{(no features detected)} \\
Z &= \{z^1\} \quad \text{(one feature } z^1 \text{ detected)} \\
Z &= \{z^1, z^2\} \quad \text{(two features } z^1, z^2 \text{ detected)} \\
& \quad \vdots \\
Z &= \{z^1, \ldots, z^3\} \quad \text{(3 features } z^1, \ldots, z^3 \text{ detected)}
\end{align*}
\] (2)

[Ronald Mahler, Lockheed Tactical Systems]
RFSs versus Vectors for SLAM

Vector Based Mapping and SLAM
PDFs of Random Finite Sets

\[ p_{k|k}\left(\mathcal{M}_k|\mathcal{Z}^k, (X^k)^{(i)}\right) \] is a multi-feature PDF which encompasses all the possibilities:

\[ p_{k|k}\left(\mathcal{M}_k|\mathcal{Z}^k, (X^k)^{(i)}\right) \rightarrow \frac{p_{k|k}\left(\emptyset|\mathcal{Z}^k, (X^k)^{(i)}\right)}{\text{prob. no features present}} \]

\[ p_{k|k}\left(\{m^1\}|\mathcal{Z}^k, (X^k)^{(i)}\right) \quad \frac{p_{k|k}\left(\{m^1\}|\mathcal{Z}^k, (X^k)^{(i)}\right)}{\text{prob. 1 feature with state } m^1} \]

\[ p_{k|k}\left(\{m^1, m^2\}|\mathcal{Z}^k, (X^k)^{(i)}\right) \quad \frac{p_{k|k}\left(\{m^1, m^2\}|\mathcal{Z}^k, (X^k)^{(i)}\right)}{\text{prob. 2 features with states } m^1, m^2} \]

\[ \vdots \]

\[ p_{k|k}\left(\{m^1, \ldots, m^{m_k}\}|\mathcal{Z}^k, (X^k)^{(i)}\right) \quad \frac{p_{k|k}\left(\{m^1, \ldots, m^{m_k}\}|\mathcal{Z}^k, (X^k)^{(i)}\right)}{\text{prob. } m_k \text{ features with states } m^1, \ldots, m^{m_k}} \]
RFS SLAM as a Generalization of RV SLAM

- **RB-PHD-SLAM vs. FastSLAM**
- **Data association**
  - In RB-PHD SLAM, all possible data associations considered by each particle
  - In FastSLAM, each particle considers one data association hypothesis
- **Map update**
  - In RB-PHD SLAM, every landmark estimate updated with every measurement, creating a set of weighted Gaussians based on measurement likelihood.
  - In FastSLAM, every landmark is updated with its associated measurement.
    
    \[ \mathcal{N}(\mu_k^i, \Sigma_k^i), \mathcal{N}(\mu_k^{i,j}, \Sigma_k^{i,j}) \]  
    \[ \forall i \in \{1 \ldots N_k^{-}\}, \forall j \in \{1 \ldots |Z_k|\} \]
  
    - The FastSLAM map is a subset of the RB-PHD SLAM map.

- **Importance Weighting**
RFS SLAM as a Generalization of RV SLAM

• Importance Weighting
  - FastSLAM:
    \[ \omega_k^{[i]} = \omega_{k-1}^{[i]} \int p \left( Z_k | x_0^{[i]}, Z_{1:k-1} \right) \]
    \[ = \omega_{k-1}^{[i]} \prod_{j=1}^{n} \int p \left( z_j^i | m^\theta(j), x_{0:k}^{[i]} \right) p \left( m^\theta(j) | x_0^{[i]}, Z_{1:k-1}, u_{1:k} \right) dm^\theta(j) \]
  - RB-PHD SLAM:
    \[ \omega_k^{[i]} = \omega_{k-1}^{[i]} \int p \left( Z_k | M_k, x_0^{[i]} \right) p \left( M_k | x_0^{[i]}, Z_{1:k-1}, u_{1:k} \right) dM_k \]

\[ \int p \left( Z_k | M_k, x_0^{[i]} \right) p \left( M_k | x_0^{[i]}, Z_{1:k-1}, u_{1:k} \right) dM_k \]
\[ = p \left( Z_k | \emptyset, x_0^{[i]}, Z_{1:k-1}, u_{1:k} \right) + \int p \left( Z_k | m^1 x_0^{[i]}, Z_{1:k-1}, u_{1:k} \right) p \left( m^1 | x_0^{[i]}, Z_{1:k-1}, u_{1:k} \right) dm^1 + \]
\[ \int \int p \left( Z_k | m^1, m^2 x_0^{[i]}, Z_{1:k-1}, u_{1:k} \right) p \left( m^1, m^2 | x_0^{[i]}, Z_{1:k-1}, u_{1:k} \right) dm^1 dm^2 + \ldots + \]
\[ \int \cdots \int p \left( Z_k | m^1, \ldots, m^m x_0^{[i]}, Z_{1:k-1}, u_{1:k} \right) p \left( m^1, \ldots, m^m | x_0^{[i]}, Z_{1:k-1}, u_{1:k} \right) dm^1 \ldots dm^m + \ldots \]

- Assume known map size
- Assume probability of detection = 1 for associated landmarks, and 0 for unassociated ones
- Then:
  \[ \int p \left( Z_k | M_k, x_0^{[i]} \right) p \left( M_k | x_0^{[i]}, Z_{1:k-1}, u_{1:k} \right) dM_k \]
  \[ = \prod_{j=1}^{n} \int p \left( z_j^i | m^\theta(j), x_0^{[i]} \right) p \left( m^\theta(j) | x_0^{[i]}, Z_{1:k-1}, u_{1:k} \right) dm^\theta(j) \]
RFSs versus Vectors for SLAM

What's in a Measurement?  
Simultaneous Localisation & Map Building  
Comparison of Vector and RFS SLAM

RFS Based Mapping and SLAM

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From Point Process Theory:

A Random Finite Set can be approximated by its first order moment – *The Intensity function* $\nu_k$ [Mahler 2003, Vo 2006].
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1. Its integral, over the set, gives the *estimated number* of elements within the set.
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\( \nu_k \) has the following properties:

1. Its integral, over the set, gives the *estimated number* of elements within the set.

2. The locations of its maxima correspond to the *estimated values* of the set members.
RFS SLAM – Intensity Function

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A Random Finite Set can be approximated by its first order moment – The Intensity function $\nu_k$ [Mahler 2003, Vo 2006].

$\nu_k$ has the following properties:

1. Its integral, over the set, gives the estimated number of elements within the set.

2. The locations of its maxima correspond to the estimated values of the set members.

Intensity function can be propagated through the Probability Hypothesis Density (PHD) filter.
Example: 1D Intensity Function (PHD)

E.g. 2 Features located at \( x=1 \) and \( x=4 \) with spatial variance: \( \sigma^2 = 1 \)
i.e. Feature set \{1, 4\} [Mahler 2007].

Suitable Gaussian Mixture PHD: 
\[
\text{PHD}(x) = \frac{1}{\sqrt{2\pi}\sigma} \left[ \exp\left( -\frac{(x-1)^2}{2\sigma^2} \right) + \exp\left( -\frac{(x-4)^2}{2\sigma^2} \right) \right]
\]
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Note: Maxima of PHD occur near $x=1$ and $x=4$ and

$$\int \text{PHD}(x) dx = 1 + 1 = 2 = \text{No. of targets!}$$
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Important Point:

A PHD is NOT a PDF, since in general it does not integrate to unity!

Note: Maxima of PHD occur near $x=1$ and $x=4$ and

$$\int \text{PHD}(x)dx = 1 + 1 = 2 = \text{No. of targets!}$$
Implementing PHD SLAM – PHD Predictor

PHD Predictor Equation:

\[ v_{k|k-1}(m|X^k) = v_{k-1|k-1}(m|X^{k-1}) + b(m|X_k) \]

Predicted PHD \quad Prior PHD \quad Birth PHD
Implementing PHD SLAM – PHD Predictor

What’s in a Measurement?  Simultaneous Localisation & Map Building  Comparison of Vector and RFS SLAM

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Implementing PHD SLAM – PHD Corrector

PHD Corrector Equation:

\[ v_{k|k}(m|X_k) = v_{k|k-1}(m|X_k)(1 - P_D(m|X_k)) \]

Posterior PHD

All predicted features weighted by their probs. missed detection

\[ + v_{k|k-1}(m|X_k) \sum_{z \in Z_k} c_k(z|X_k) + \int_{\xi \in \mathcal{M}_k} \Lambda(\xi|X_k) v_{k|k-1}(\xi|X_k) d\xi \]

All predicted features, updated by the spatial locations of all the new measurements, and their probabilities of detection
Implementing PHD SLAM – PHD Corrector

What's in a Measurement?  Simultaneous Localisation & Map Building  Comparison of Vector and RFS SLAM

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Implementing PHD SLAM – Particle updates

RB PHD SLAM:

\[
\left\{ \eta_{k-1}^{(i)}, (X^{k-1})^{(i)} \right\}, \left\{ \mu_{k-1|k-1}^{(j)}, P_{k-1|k-1}^{(j)}, w_{k-1|k-1}^{(j)} \right\}^{j=1}_{j=1} J_{k-1|k-1}^{(i)} \right\}^{N}_{i=1}
\]

Prior GM-PHD

\[v_{k-1|k-1}^{(i)}(m|(X^{k-1})^{(i)})\]

\[\rightarrow \left\{ \eta_{k}^{(i)}, (X^{k})^{(i)} \right\}, \left\{ \mu_{k|k}^{(j)}, P_{k|k}^{(j)}, w_{k|k}^{(j)} \right\}^{j=1}_{j=1} J_{k|k}^{(i)} \right\}^{N}_{i=1}
\]

Posterior GM-PHD

\[v_{k|k}^{(i)}(m|(X^{k})^{(i)})\]
Implementing PHD SLAM – SLAM EAP Map

**Inputs:**
- All $N$ updated trajectory particle weights
  \[ \eta_k^{1}, \eta_k^{2}, \ldots, \eta_k^{N} \]
- All $N$ updated trajectory particles
  \[ (X^k)^1, (X^k)^2, \ldots, (X^k)^N \]
- All map PHDs associated with each particle
  \[ v_{k|k}^{(1)}, v_{k|k}^{(2)}, \ldots, v_{k|k}^{(N)} \]

**Filtering actions:**
- Calculate average particle weight
  \[ \bar{\eta}_k = \sum_{j=1}^{N} \eta_k^{(j)} \]
- Calculate weighted average trajectory particle
  \[ X^k = \frac{1}{\bar{\eta}_k} \sum_{j=1}^{N} \eta_k^{(j)} (X^k)^{(j)} \]
- Calculate weighted average map GM–PHD
  \[ v_{k|k} (m|X^k) = \frac{1}{\bar{\eta}_k} \sum_{j=1}^{N} v_{k|k}^{(j)} (m|X^k)^{(j)} \]

**Output:**
- Final SLAM estimate
  - Final trajectory particle estimate
    \[ X^k \]
  - Final GM–PHD map estimate
    \[ v_{k|k} (m|X^k) \]

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C++ Library for RFS SLAM

- Open source, with BSD-3 License
- Dependencies:
  - Boost::math_c99 1.48
  - Boost::timer 1.48
  - Boost::system 1.48
  - Boost::thread 1.48
  - Eigen3
- Tested on Ubuntu 13.04
- Template library
  - Define your own process models
  - Define your own measurement models
- Includes an implementation of the RB-PHD Filter
- Includes a 2-d SLAM example
- Well documented
- Will be updated with new published research
- Download at: https://github.com/kykleung/RFS-SLAM
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   • A Random Finite Set (RFS) Approach.
   • PHD SLAM – Implementation.

3. Comparison of Vector Based SLAM (MH–FastSLAM) and PHD–SLAM – Results.
Comparative results for the proposed GM–PHD SLAM filter (black) and that of FastSLAM (red), compared to ground truth (green).
The raw dataset at a clutter density of 0.03 m$^{-2}$. 
The estimated trajectories of the GM–PHD SLAM filter (black) and that of FastSLAM (red). Estimated feature locations (crosses) are also shown with the true features (green circles).
What’s in a Measurement?        Simultaneous Localisation & Map Building        Comparison of Vector and RFS SLAM

RFS Versus Vector Based SLAM

Feature number estimates.
Sample data registered from radar.
RFS Versus Vector Based SLAM

SLAM input: Odometry path + radar data

Extracted point feature measurements registered to odometry.
RFS Versus Vector Based SLAM

NN–EKF

FastSLAM

PHD–SLAM

EKF, FastSLAM and PHD–SLAM with Radar data.

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Singapore – MIT Alliance: CENSAM Project

- Environmental monitoring of coastal waters.
- Navigation and map info. necessary above/below water surface.
- Fusion of sea surface radar, sub–sea sonar data for combined surface/sub–sea mapping.
Singapore – MIT Alliance: CENSAM Project
Singapore – MIT Alliance: CENSAM Project

Coastal Mapping, Surveillance, HARTS / AIS verification

Mobile platform can remove blind spots from land-based radar.

Video: CoastalModelling.avi

Video: CoastalandAIS.avi
RFS Versus Vector Based SLAM

GPS Trajectory (Green Line), GPS point feature coordinates (Green Points), Point feature measurement history (Black dots).
RFS Versus Vector Based SLAM

Top: Posterior MHT SLAM estimate (red).
Bottom: Posterior RB–PHD SLAM estimate (blue).
Ground truth (Green).
(Red) MHT SLAM Feature Number estimate.
(Blue) PRB–PHD SLAM Feature Number Number estimate.
(Green) Actual Number to enter FoV at each time index.
1. Feature based maps more appropriately modelled as RFS than a random vector.

2. RFS Frameworks take into account detection as well as spatial uncertainty information.

3. PHD Filter approximation demonstrated – circumvents fragile data association necessary in vector based methods.

4. Superior results in cluttered environments.
Acknowledgements


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