Robotic Navigation - Experience Gained with RADAR

Martin Adams
Dept. Electrical Engineering, AMTC
Universidad de Chile (martin@ing.uchile.cl)

2nd Workshop on Alternative Sensing for Robot Perception – IROS 2015
1. Mapping, Tracking & SLAM at U. Chile.

2. Sensor Measurement & Detections:
   • Landmark Existence and Spatial Uncertainty.

3. Simultaneous Localisation & Map Building (SLAM).
   • A Random Finite Set (RFS) Approach.
   • Set Based Likelihood Formulation.
   • RFS SLAM – A generalization of Random Vector SLAM.
   • RFS versus Vector Based SLAM – Results.

4. Future Work in RFS based Mapping/SLAM.
Presentation Outline

1. Mapping, Tracking & SLAM at U. Chile.

2. Sensor Measurement & Detections:
   - Landmark Existence and Spatial Uncertainty.

3. Simultaneous Localisation & Map Building (SLAM).
   - Set Based Likelihood Formulation.
   - RFS SLAM – A generalization of Random Vector SLAM.
   - RFS versus Vector Based SLAM – Results.

4. Future Work in RFS based Mapping/SLAM.
Mapping El Teniente’s Esmeralda Mine. – VIDEO
Mapping in Mines/Rugged Terrains

Individual LADAR scans

Registered LADAR scans from 45 individual scans
Space Debris Tracking

Detecting & Tracking space debris between 1 and 10 cubic cm based on optical & radio telescopic data

Vicuña (Chile) NEO Space telescope (U. Chile + U. Serena)

Chilbolton 3GHz range/Doppler radar for SSA
Space Debris Tracking

Goals: Provide tracking SW framework robust to significant false alarms & radar/visual blind zones
SLAM in outdoor/mining environments

2nd Workshop on Alternative Sensing for Robot Perception – IROS 2015
SLAM in outdoor/mining environments

- Improved estimation and incorporation of detection statistics & measurement likelihoods in RFS based SLAM

2\textsuperscript{nd} Workshop on Alternative Sensing for Robot Perception – IROS 2015
Presentation Outline

1. Mapping, Tracking & SLAM at U. Chile.

2. Sensor Measurement & Detections:
   - Landmark Existence and Spatial Uncertainty.

3. Simultaneous Localisation & Map Building (SLAM).
   - Set Based Likelihood Formulation.
   - RFS SLAM – A generalization of Random Vector SLAM.
   - RFS versus Vector Based SLAM – Results.

4. Future Work in RFS based Mapping/SLAM.
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

Video El Teniente
Sensing the Environment: Detection Errors

The random nature of detections

(a) Radar point detections based on an OS-CFAR detector.

Radar

LRF + Line

RANSAC

(b) Laser range data with a single RANSAC line detector

Visual

SURF Features

(c) Visual SURF features.
Sensing the Environment: Detection Statistics

Feature absence & presence statistics

(a) MMW FMCW radar detections
Scaled distributions:
- Feature absent
- Feature present
Possible detection threshold

(b) Laser range finder RANSAC line detections
Scaled distributions:
- Feature absent
- Feature present
Possible detection threshold

(c) Image based SURF feature detections
Scaled distributions:
- Feature absent
- Feature present
Possible detection threshold

Radar
LRF + Line
RANSAC
Visual
SURF Features

Mapping, Tracking & SLAM at U. Chile
Sensor Measurements & Detections
SLAM
Future Work in RFS Based SLAM

2nd Workshop on Alternative Sensing for Robot Perception – IROS 2015
What’s in a Measurement?

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

Received Power

Distance / m

10 20 30 40 50 60 70 80 90 100
What’s in a Measurement?

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

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

CFAR Threshold

2nd Workshop on Alternative Sensing for Robot Perception – IROS 2015
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
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:

Result: Detection decision at range $r_k^i$

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

Subtly assumes unity detection probability $P_D = 1$
What’s in a Measurement?

Robotic Interpretation:

Radar Interpretation:

Result:

Detection decision at range \( r_k^i \)

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

Subtly assumes unity detection probability \( P_D = 1 \)
What’s in a Measurement?

Robotic Interpretation:

- A-Scope display at chosen radar bearing angle
- Spatial interpretation: Area under dist. = 1
- Result: Detection decision at range \( r^i_k \)
- A-priori range uncertainty assumed/known \((\sigma^2_k)^i\)
- Subtly assumes unity detection probability \( P_D = 1 \)

Radar Interpretation:

- Detection theory applied to A-Scope from (a)
- CFAR Threshold
- (c) Detection Information
- (e) Detection Information
- Multiple detection hypotheses \( H_1(r(q)) \)
- Associated probabilities of detection \( P_D \)
- Associated probability of false alarm \( P_{fa} \)

2\textsuperscript{nd} Workshop on Alternative Sensing for Robot Perception – IROS 2015
What’s in a Measurement?

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

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

(i.e. range, spatial uncertainty, detection uncertainty and false alarm probability).
The Importance of Missed Detections

- Wider beam width
- Foliage penetration
The Importance of False Alarms

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

Video: Raw_Data_Display.avi
Radar vs. Ladar

Sample of NTU University Campus Dataset
Note the rich data output due to the multi-target detection capabilities of the radar, to those of the laser.
1. Mapping, Tracking & SLAM at U. Chile.

2. Sensor Measurement & Detections:
   - Landmark Existence and Spatial Uncertainty.

3. Simultaneous Localisation & Map Building (SLAM).
   - Set Based Likelihood Formulation.
   - RFS SLAM – A generalization of Random Vector SLAM.
   - RFS versus Vector Based SLAM – Results.

4. Future Work in RFS based Mapping/SLAM.
In an unknown environment – robot & feature positions *must* be estimated simultaneously – SLAM.

- SLAM is a probabilistic algorithm

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

- \( x_t \) = State of the robot at time \( t \)
- \( m \) = Map of the environment
- \( z_{1:t} \) = Sensor inputs from time 1 to \( t \)
- \( u_{1:t} \) = Control inputs from time 1 to \( t \)

- Update distribution estimate with Bayes theorem.
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:

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

\[ M = [m_1, m_2, m_3, m_4, m_5, m_6, m_7] \]
A Random Finite Set (RFS) Approach

Untangle:
\[ Z = [z_1, z_2, z_3, z_4, z_5, z_6, z_7] \]
\[ M = [m_1, m_2, m_3, m_4, m_5, m_6, m_7] \]
A Random Finite Set (RFS) Approach

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.
What is a RFS Measurement?

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

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:

\[
\begin{align*}
Z &= \emptyset & \text{(no features detected)} \\
Z &= \{z^1\} & \text{(one feature } z^1 \text{ detected)} \\
Z &= \{z^1, z^2\} & \text{(two features } z^1, z^2 \text{ detected)} \\
& \vdots & \vdots & \vdots \\
Z &= \{z^1, \ldots, z^3\} & \text{(3 features } z^1, \ldots, z^3 \text{ detected)}
\end{align*}
\]
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 missions...
RFSs versus Vectors for SLAM

Vector Based Mapping and SLAM

2nd Workshop on Alternative Sensing for Robot Perception – IROS 2015
RFSs versus Vectors for SLAM

Mapping, Tracking & SLAM at U. Chile
Sensor Measurements & Detections
SLAM
Future Work in RFS Based SLAM

RFS Based Mapping and SLAM

Sensor Data

Feature extraction

Observed feature set at time \( k+1 \)

\( \{f_1, f_2, f_3, \ldots, f_m\} \)

Predicted feature state set at time \( k \)

\( \{f_1, f_2, f_3, \ldots, f_n\} \)

State representation ready for prediction at time \( k+1 \).

Sets mathematically represented in terms of feature number and their attributes (locations).

Bayes optimality based on all \( m \) observations and all \( n \) previous state estimates.

Statistical representation of the set (eg. Intensity function)

Bayes Estimator (eg. PHD, CPHD, etc)

Statistical representation of the set estimate (eg. updated intensity function)

Possible to reconstruct updated feature set with updated number of elements & their attributes (locations)

2nd Workshop on Alternative Sensing for Robot Perception – IROS 2015
SLAM Formulations

- System model:
  \[ x_k = g(x_{k-1}, u_k, \delta_k) \]
  \[ z^j_k = h(x_k, m^i_k, \epsilon_k) \]

  \[ \mathcal{Z}_k \equiv \{ z^1_k, z^2_k, \ldots, z^{n_k}_k \} \]

  - Bayes filter
    \[ p(x_{0:k}, m_k | Z_{1:k-1}, u_{0:k}, \theta_{1:k-1}) \]
    \[ = p(x_k | x_{k-1}, u_k) p(x_{0:k-1}, m_k | Z_{1:k-1}, u_{0:k-1}, \theta_{1:k-1}) \]
    \[ p(x_{0:k}, m_k | Z_{1:k}, u_{0:k}, \theta_{1:k}) \]
    \[ = \frac{p(Z_k | x_{0:k}, m_k, \theta_k) p(x_{0:k}, m_k | Z_{1:k-1}, u_{0:k}, \theta_{1:k-1})}{\int p(Z_k | x_{0:k}, m_k, \theta_k) p(m_k | Z_{1:k-1}, x_{0:k}, \theta_{1:k-1}) \, dm_k} \]

  - Batch estimation
    \[ \arg \max_{x_{0:k}, m_k} p(x_{0:k}, m_k | Z_{1:k}, u_{0:k}, \theta_{1:k}) \]
    \[ = \arg \max_{x_{0:k}, m_k} p(x_{0:k}, m_k) \prod_{l=1}^{k} p(Z_l | x_l, m_k, \theta_l) p(x_l | x_{l-1}, u_l) \]
SLAM Formulations

- **RFS-based formulations:**
  \[ p(\mathbf{x}_{0:k}, \mathcal{M}_{k}|\mathcal{Z}_{1:k-1}, \mathbf{u}_{0:k}) \]

  - **Bayes filter**
    \[ p(\mathbf{x}_{0:k}, \mathcal{M}_{k}|\mathcal{Z}_{1:k-1}, \mathbf{u}_{0:k}) = p(\mathbf{x}_{k}|\mathbf{x}_{k-1}, \mathbf{u}_{k}) p(\mathbf{x}_{0:k-1}, \mathcal{M}_{k}|\mathcal{Z}_{1:k-1}, \mathbf{u}_{0:k-1}) \]

  - **Batch estimation**
    \[
    \arg\max_{\mathbf{x}_{0:k}, \mathcal{M}_{k}} p(\mathbf{x}_{0:k}, \mathcal{M}_{k}|\mathcal{Z}_{1:k}, \mathbf{u}_{0:k})
    = \arg\max_{\mathbf{x}_{0:k}, \mathcal{M}_{k}} p(\mathbf{x}_{0:k}, \mathcal{M}_{k}) \prod_{l=1}^{k} p(\mathcal{Z}_{l}|\mathbf{x}_{l}, \mathcal{M}_{k}) p(\mathbf{x}_{l}|\mathbf{x}_{l-1}, \mathbf{u}_{l})
    \]

- Need to examine the relationship between the RFS and random-vector forms of the high-lighted distributions.
SLAM Pose/Map Distribution

- Janossy density for RFS
  
  \[ p(x_{0:k}, \mathcal{M}_k | Z_{1:k-1}, u_{0:k}) \]
  
  \[ = m! \, p_{|\mathcal{M}_k|}(m) \, p(x_{0:k}, (m_1^1, \ldots, m_k^m) | Z_{1:k-1}, u_{0:k}) \]

- Pick 1 / \( m! \) possible map ordering
- Fix the map size to \( m \), such that the cardinality distribution: \( p_{|\mathcal{M}_k|}(m) = 1 \)

\[
\frac{1}{m!} p(x_{0:k}, \mathcal{M}_k | Z_{1:k-1}, u_{0:k}, \theta_{1:k-1}), \quad p_{|\mathcal{M}_k|}(m) = 1
\]

\[ = p(x_{0:k}, (m_1^1, m_2^2, \ldots, m_k^m) | Z_{1:k-1}, u_{0:k}, \theta_{1:k-1}) \]

\[ = p(x_{0:k}, m_k | Z_{1:k-1}, u_{0:k}, \theta_{1:k-1}) \]
SLAM Normalizing Factor

- Set integral:
  \[
  \int p\left(Z_k, M_k \mid x_{0:k}, Z_{1:k-1}\right) dM_k
  \]
  \[= p\left(Z_k, \emptyset \mid x_{0:k}, Z_{1:k-1}\right) + \int p\left(Z_k, \{m^1_k\} \mid x_{0:k}, Z_{1:k-1}\right) dm^1_k
  \]
  \[+ \frac{1}{2!} \int \int p\left(Z_k, \{m^1_k, m^2_k\} \mid x_{0:k}, Z_{1:k-1}\right) dm^1_k dm^2_k + \ldots
  \]
  \[+ \frac{1}{m!} \int \cdots \int p\left(Z_k, \{m^1_k, \ldots, m^m_k\} \mid x_{0:k}, Z_{1:k-1}\right) dm^1_k \ldots dm^m_k + \ldots
  \]

- Fix the map size:
  \[
  \int p\left(Z_k, M_k \mid x_{0:k}, Z_{1:k-1}\right) dM_k, \quad \text{given } |M_k| = m
  \]
  \[= \frac{1}{m!} \int \cdots \int p\left(Z_k, \{m^1_k, \ldots, m^m_k\} \mid x_{0:k}, Z_{1:k-1}\right) dm^1_k \ldots dm^m_k
  \]
  \[= \frac{1}{m!} \int \cdots \int p\left(Z_k, (m^1_k, \ldots, m^m_k) \mid x_{0:k}, Z_{1:k-1}\right)
  \]
  \[\times m! \cdot p_{M_k}(m) \ dm^1_k \ldots dm^m_k
  \]
  \[= \int \cdots \int p\left(Z_k, (m^1_k, \ldots, m^m_k) \mid x_{0:k}, Z_{1:k-1}\right) dm^1_k \ldots dm^m_k
  \]

2nd Workshop on Alternative Sensing for Robot Perception – IROS 2015
SLAM Measurement Likelihood

- Multi-target likelihood

\[
p(Z_k|M_k, x_{0:k}) = p_\kappa(Z_k) \prod_i (1 - P_D(x_k, m^i)) \sum_\theta \prod_{j=1}^{Z_k} \frac{P_D(x_k, m^{\theta_j}) p(z^j|m^{\theta_j}, x_{0:k})}{(1 - P_D(x_k, m^{\theta_j})) \lambda_\kappa p_\kappa(z^j)}, \quad p_\kappa(\cdot) \text{ is Poisson}
\]

\[
= p_\kappa(Z_k) \prod_i (1 - P_D(x_k, m^i)) \sum_\theta \left( p(Z_k^\theta|M_k^\theta, x_{0,k}, \theta) \prod_{m \in M_k^\theta} \frac{P_D(x_k, m)}{(1 - P_D(x_k, m))} \prod_{z \in Z_k^\theta} \frac{1}{(1 - p_\kappa(z))} \right)
\]

\[
= \sum_\theta \left( p(Z_k^\theta|M_k^\theta, x_{0,k}, \theta) \prod_{m \in M_k^\theta} P_D(x_k, m) \prod_{m \in \overline{M_k^\theta}} (1 - P_D(x_k, m)) p_\kappa(Z_k^\theta) \right)
\]
Select one data association hypothesis $\theta^*$.  

$$p(Z_k^\theta | M_k^\theta, x_{0,k}, \theta) = 0 \quad \text{if } \theta \neq \theta^*$$

$$p(Z_k, M_k, x_{0:k}) = p\left(Z_k^{\theta^*} | M_k^{\theta^*}, x_{0,k}, \theta^*\right) \prod_{m \in M_k^\theta} P_D(x_k, m) \prod_{m \in M_k^\theta} (1 - P_D(x_k, m)) p_\kappa(Z_k^{\theta^*})$$

Assume for all associated landmarks that

$$P_D(x_k, m) = \begin{cases} 1 & \text{if } m \in M_k^{\theta^*} \\ 0 & \text{otherwise} \end{cases}$$

$$p(Z_k, M_k, x_{0:k}) = p\left(Z_k^{\theta^*} | M_k^{\theta^*}, x_{0,k}, \theta^*\right) p_\kappa(Z_k^{\theta^*})$$

In addition, for all non-associated measurements, assume $p_\kappa(Z_k^{\theta^*}) = 1$

$$p(Z_k, M_k, x_{0:k}) = p\left(Z_k^{\theta^*} | M_k^{\theta^*}, x_{0,k}, \theta^*\right) = p\left(Z_k^{\theta^*} | m_k, x_{0,k}, \theta^*\right)$$

Random-vector measurement likelihood
The RFS formulation is equivalent to the vector-based formulation when:

- Map size is fixed / deterministic (with one ordering)
- Data association is assumed
- Probability of detection equals 1 for associated landmarks
- Probability of non-associated measurements being clutter equals 1

RFS–SLAM is a generalization of random-vector SLAM
How to do RFS SLAM – PHD Approximation

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].
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].

\( \nu_k \) has the following properties:
RFS SLAM – Intensity Function

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].

$\nu_k$ has the following properties:

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

$\nu_k$ 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

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].

$\nu_k$ 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: 

$$\text{PHD}(x) = \frac{1}{\sqrt{2\pi}\sigma} \left[ \exp \left( -\frac{(x-1)^2}{2\sigma^2} \right) + \exp \left( -\frac{(x-4)^2}{2\sigma^2} \right) \right]$$
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:  

$$
PHD(x) = \frac{1}{\sqrt{2\pi\sigma}} \left[ \exp\left(-\frac{(x-1)^2}{2\sigma^2}\right) + \exp\left(-\frac{(x-4)^2}{2\sigma^2}\right) \right]
$$

![Graph of PHD function]
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:

\[
\text{PHD}(x) = \frac{1}{\sqrt{2\pi\sigma}} \left[ \exp \left( -\frac{(x-1)^2}{2\sigma^2} \right) + \exp \left( -\frac{(x-4)^2}{2\sigma^2} \right) \right]
\]

Note: Maxima of PHD occur near \( x=1 \) and \( x=4 \) and

\[
\int \text{PHD}(x)\,dx = 1 + 1 = 2 = \text{No. of targets!}
\]
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: 

$$\text{PHD}(x) = \frac{1}{\sqrt{2\pi\sigma}} \left[ \exp\left(-\frac{(x-1)^2}{2\sigma^2}\right) + \exp\left(-\frac{(x-4)^2}{2\sigma^2}\right) \right]$$

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

$$\int \text{PHD}(x)dx = 1 + 1 = 2 = \text{No. of targets!}$$
Gaussian mixture representation of intensity function, showing peaks at feature locations at time \(k-1\).
Notice 2 features at \((5, -8)\) represented by single, unresolved Gaussian with mass 2.
Black crosses show true feature locations.
Gaussian mixture representation of intensity function at time $k$. Peaks at feature locations $(5, -8)$ now resolved – 2 Gaussians, mass 1.

Note feature at $(-5, -4)$ has reduced local mass, due to a small likelihood over all measurements.
Comparative results for the proposed GM–PHD SLAM filter (black) and that of FastSLAM (red), compared to ground truth (green).
RFS Versus Vector Based SLAM

The raw dataset at a clutter density of 0.03 m$^{-2}$. 

2nd Workshop on Alternative Sensing for Robot Perception – IROS 2015
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).
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.

2nd Workshop on Alternative Sensing for Robot Perception - IROS 2015
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.

Autonomous Kayak Surface Vehicle with Radar
Singapore – MIT Alliance: CENSAM Project
Singapore – MIT Alliance: CENSAM Project

- Surface and sub-sea data.
- Verification of radar/sonar data with coastal satellite images.
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
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).
RFS Versus Vector Based SLAM

(Red) MHT SLAM Feature Number estimate.
(Blue) PRB–PHD SLAM Feature Number Number estimate.
(Green) Actual Number to enter FoV at each time index.
RFS Versus Vector Based SLAM

Results based on multi-feature strategy:

Videos:

Victoria park with added clutter (21,500 clutter detections)

MH–FastSLAM with clutter

RB–PHD–SLAM with clutter.

Parque O’Higgins with “natural” clutter

MH–FastSLAM with clutter (joggers in park)

RB–PHD–SLAM with clutter.
• **Objective:** Show that *Random Finite Set (RFS) SLAM* is a generalization of the random–vector based SLAM formulation

• **Approach:** Mathematically show that the *RFS Bayes Filter* can be reduced to the Bayes filter in its random–vector form, under a set of *ideal detection conditions*.  
  - This can also be shown for the batch estimation approach / formulation

• **Ideal Detection Conditions:**  
  - Perfect detection of landmarks  
  - No clutter / false alarms  
  - Map size is deterministic  
  - Assumed data association hypothesis
RFS Versus Vector Based SLAM

• Importance of findings:
  – Understanding of why RFS–based SLAM algorithms perform better under non–ideal detection conditions
  – Understanding of why vector–based SLAM algorithms perform better under ideal detection conditions

• Experimental Validation:
  – Ideal vs. non–ideal detection conditions
  – RB–PHD–SLAM vs. FastSLAM
  – Simulations and real datasets
RFS Versus Vector Based SLAM

Close to ideal conditions
FastSLAM  
RB–PHD–SLAM

Non-ideal conditions
FastSLAM  
RB–PHD–SLAM

Mapping, Tracking & SLAM at U. Chile  
Sensor Measurements & Detections  
SLAM  
Future Work in RFS Based SLAM

2nd Workshop on Alternative Sensing for Robot Perception – IROS 2015
Presentation Outline

1. Mapping, Tracking & SLAM at U. Chile.

2. Sensor Measurements & Detections:
   • Landmark Existence and Spatial Uncertainty.

3. Simultaneous Localisation & Map Building (SLAM).
   • A Random Finite Set (RFS) Approach.
   • Set Based Likelihood Formulation.
   • RFS SLAM – A generalization of Random Vector SLAM.
   • RFS versus Vector Based SLAM – Results.

4. Future Work in RFS based Mapping/SLAM.
Conclusions & Future Work

1. Improve robustness of autonomous sensing systems.

2. Probabilistic sensor modelling – improve estimates of detection statistics, e.g. – based on occlusions.

3. Other FISST SLAM techniques based on Labelled Multi–Bernoulli (MeMBer) Filter.

4. Metrics beyond OSPA for the intuitive evaluation and comparison of SLAM maps.
Acknowledgements

The Research Teams:

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