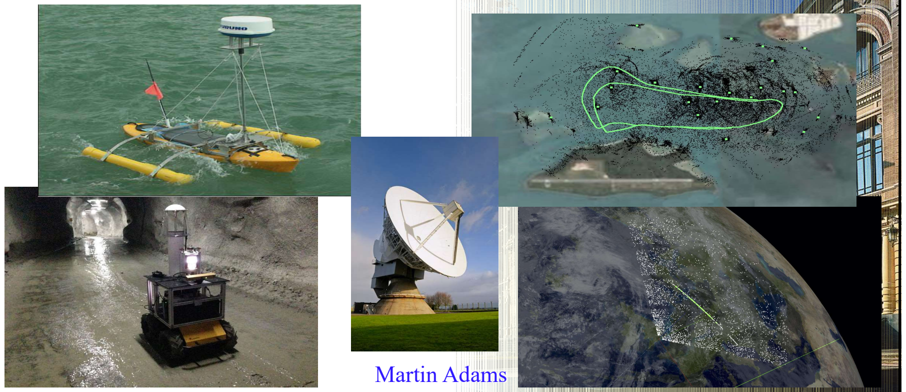
Lessons from Radar: New Approaches in Autonomous Navigation & Tracking



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Presentation Outline

1. Radar-Based SLAM & Multi-Target Tracking.
2. Lessons from Radar – Random Finite Set (RFS) Formulations.
   - Motivation for new Mapping/SLAM concepts.
3. Simultaneous Localisation & Mapping (SLAM) with RFSs.
   - Relation between RFS and RV-SLAM
   - RFS versus Random Vector (RV)-SLAM Results.
4. Future Work in RFS based Mapping/SLAM.

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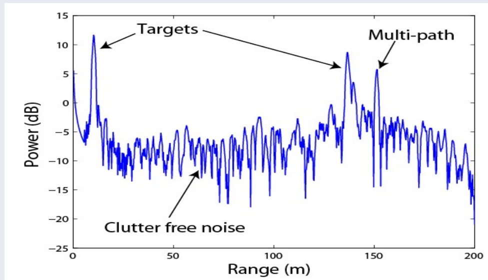
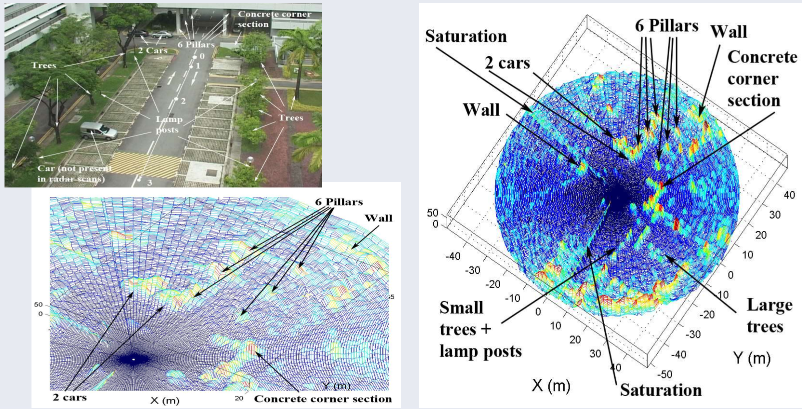
Radar: From Signal to Detection

Millimetre Wave Radar

- 360 deg. scanning unit, 77GHz FMCW
- 0.25m range res., 200m max range
- Per Bearing angle -> Multiple Targets
- 1.8 deg. beam width

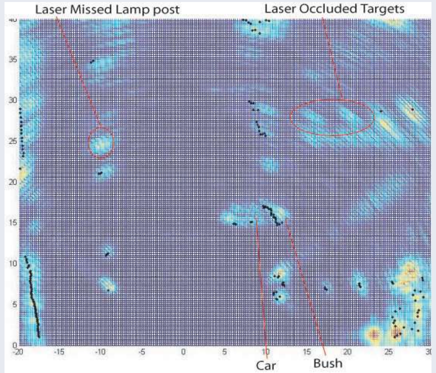


Radar: From Signal to Detection



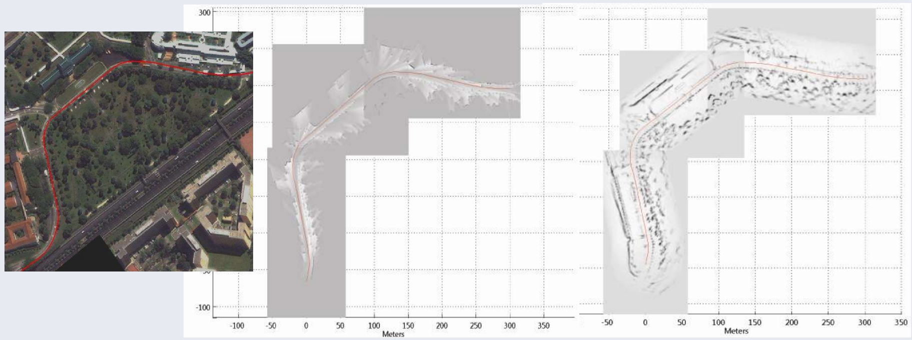
Radar versus Ladar

Radar: Wider beam width, Foliage penetration



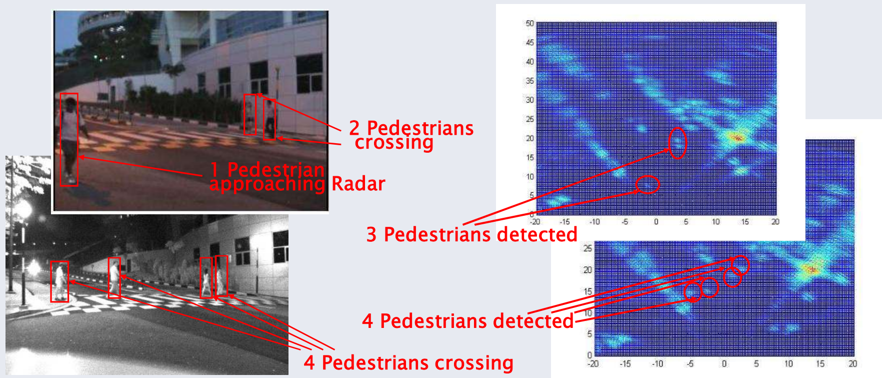
Radar versus Ladar

Sample of NTU University Campus Dataset: Greater penetration, more detailed maps.

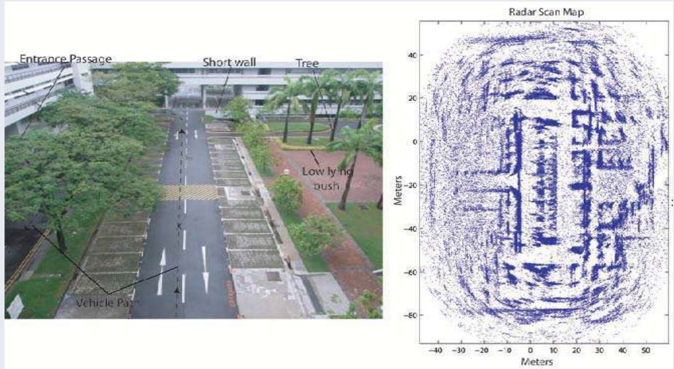


People Detection at Road Junctions

Road crossing environment (Near IR image Vs. Radar image)



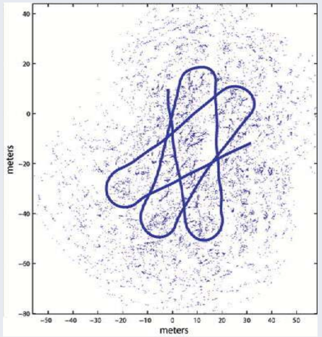
SLAM with MMW Radar



Sample data registered from radar.

SLAM with MMW Radar

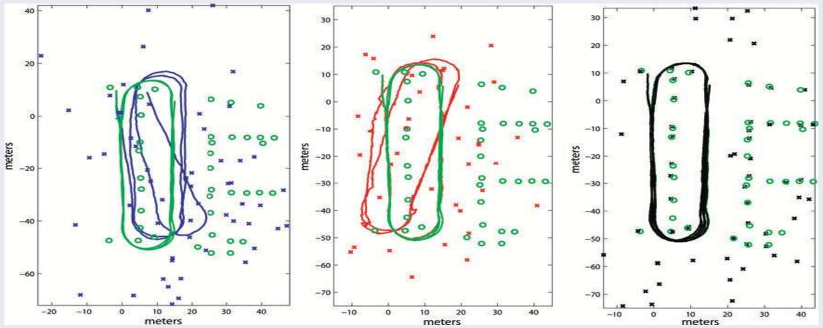
SLAM input: Odometry path + radar data



Extracted point feature measurements registered to odometry.

SLAM with MMW Radar

NN-EKF FastSLAM PHD-SLAM

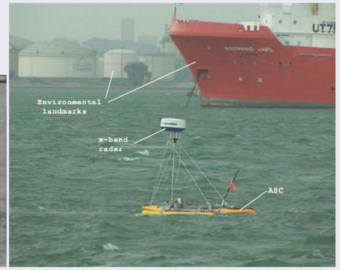


EKF, FastSLAM and PHD-SLAM with Radar data.

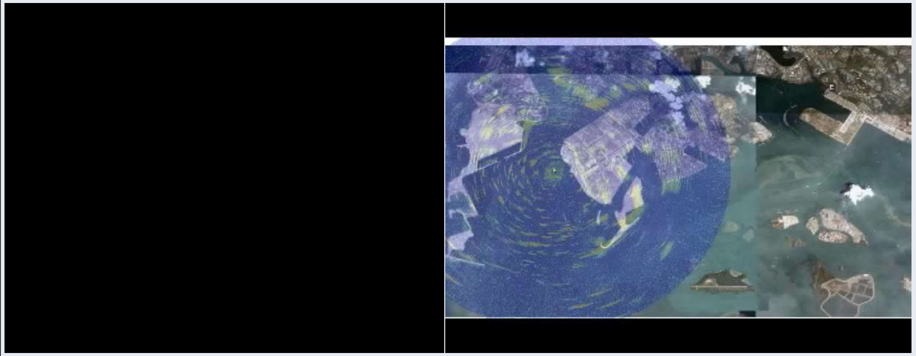
SLAM with Marine Radar: Singapore – MIT Alliance: CENSAM Project

- 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.

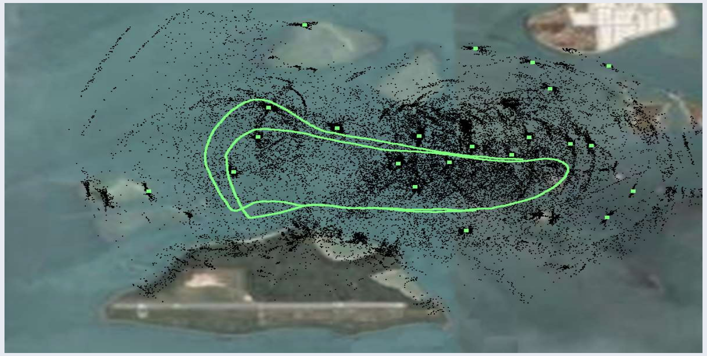
Autonomous Kayak Surface Vehicle with Radar



SLAM with Marine Radar: Singapore – MIT Alliance: CENSAM Project

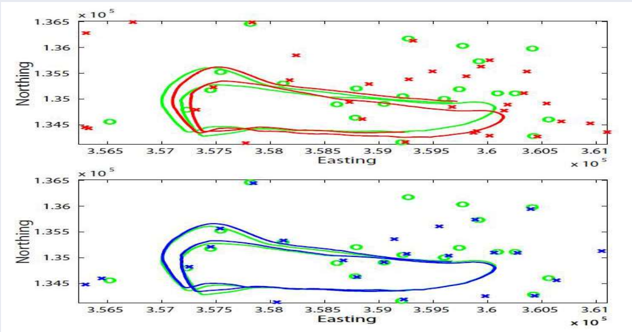


RFS Versus Vector Based SLAM



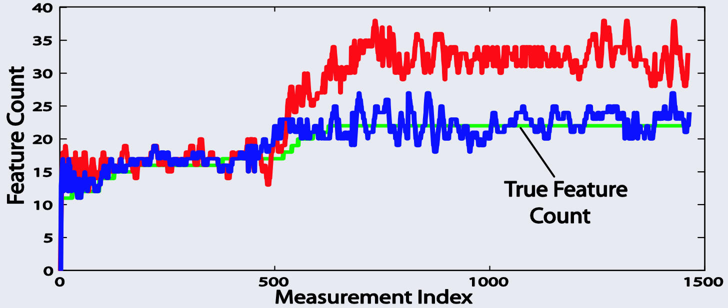
GPS Trajectory (Green Line), GPS point feature coordinates (Green Points), Point feature measurement history (Black dots).

RFS Versus Vector Based SLAM



Top: Posterior MH-FastSLAM estimate (red).
Bottom: Posterior RB-PHD SLAM estimate (blue).
Ground truth (Green).

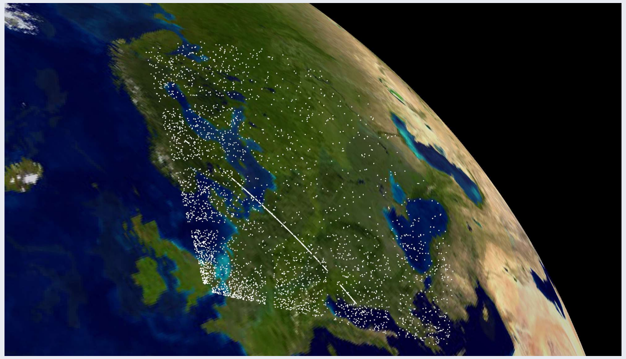
RFS Versus Vector Based SLAM



(Red) MH-FastSLAM Feature Number estimate.
(Blue) PRB-PHD SLAM Feature Number estimate.
(Green) Actual Number to enter FoV at each time index.

Space Situational Awareness – Space Debris Tracking

Chilboton LEO CAMRa

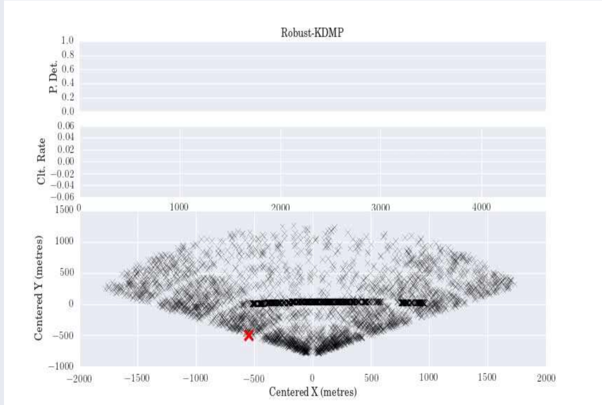


Radar detections from south U.K: Defunct ADEOS II pass.

[3] A. Pak, J. Correa, M. Adams, "*Robust Joint Target Detection and Tracking for Space Situational Awareness*", Journal of Guidance, Control and Dynamics, Vol. 41, No. 1, Jan. 2018.

Radar-Based SLAM & MTT | Lessons from Radar - RFSs | RFS-SLAM | Future Work in RFS Based SLAM

Preliminary Results: Space Debris tracking



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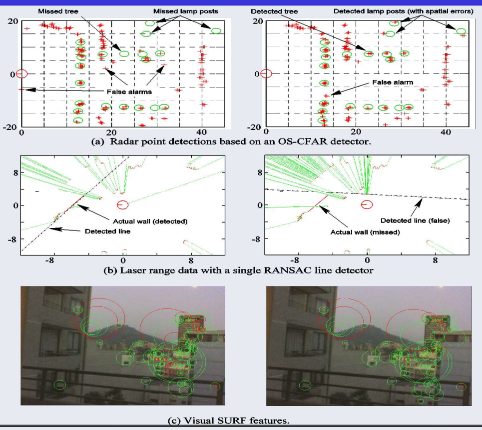
Sensing the Environment

Clearpath Robotic Skid Steer Platform

- ➢Acumine Radar 360 deg. scanning unit, 94GHz FMCW
- ➢Sick LD-LRS1000 Scanning LRF
- ➢Microsoft Kinect camera system

Sensing the Environment: Detection Errors

The random nature of detections

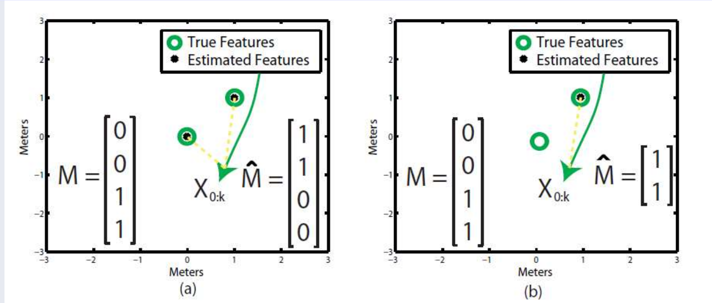


Radar

LRF + Line RANSAC

Visual SURF Features

Back to Basics: Why Random Finite Sets? Robotic Mapping Error

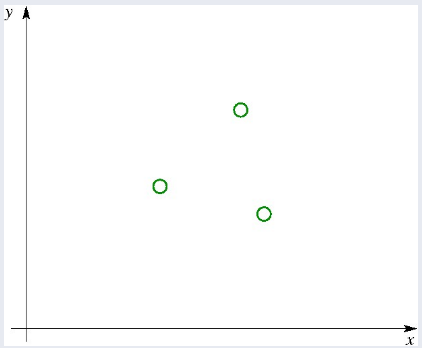


Map error: $||M - \widehat{M}|| = 2$ $\qquad ||M - \widehat{M}|| = ???$

Set based error metrics exist: Haussdorf, OMAT, OSPA[1], COLA[2]...

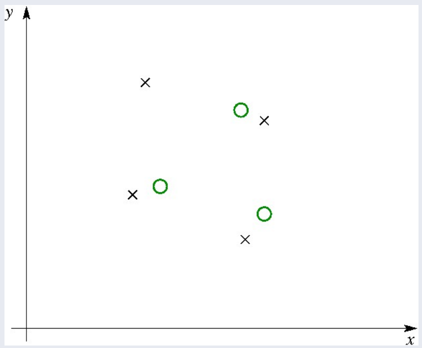
[6] D. Schumacher, B.-T. Vo, B.-N. Vo, "A Consistent Metric for Performance Evaluation of Multi-Object Filters", IEEE Trans. Signal Proc. Vol 56, No. 8, pages 3447 - 3457, 2008.
[7] P. Barrios, M. Adams, et al, "Metrics for Evaluating Feature-Based Mapping Performance" IEEE Transactions on Robotics, Vol. 33, No. 1, pages 198 to 213, February 2017.

Why Random Finite Sets? Robotic Mapping Error



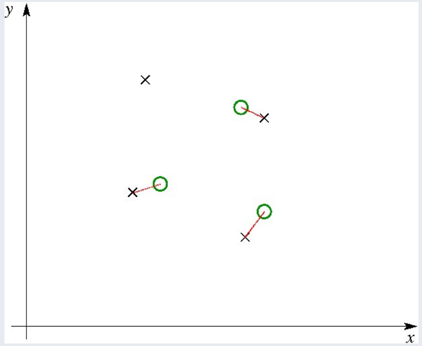
- Ground truth feature/target map.

Why Random Finite Sets? Robotic Mapping Error



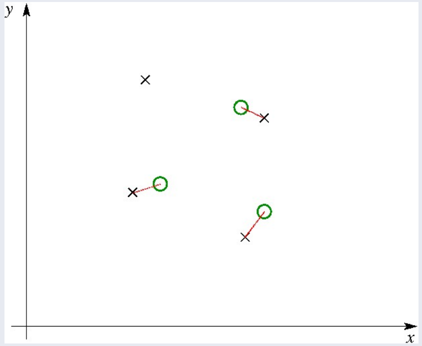
- Ground truth feature/target map.
- Map estimate.

Why Random Finite Sets? Robotic Mapping Error



- Ground truth feature/target map.
- Map estimate.
- Data asscociation & map management

Why Random Finite Sets? Robotic Mapping Error



- Ground truth feature/target map.
- Map estimate.
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- Result: Can now specify map error (e.g. average Euclidean distance between associated features).

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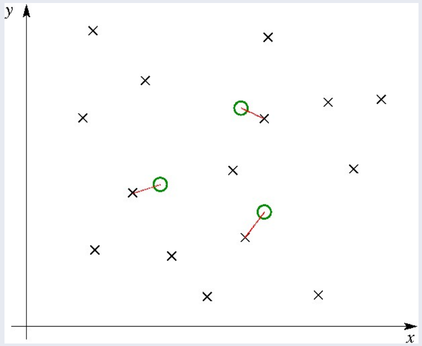
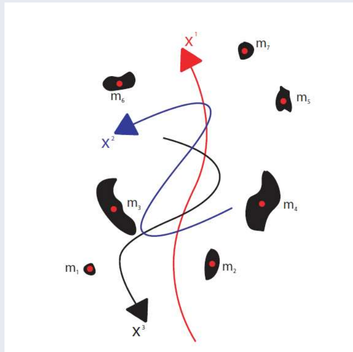


- Ground truth feature/target map.
- Map estimate.
- Data asscociation & map management
- Result: Can now specify map error (e.g. average Euclidean distance between associated features).
- However, this map estimate would give the same error, despite many more false positives.

What's Wrong with Random Vectors?



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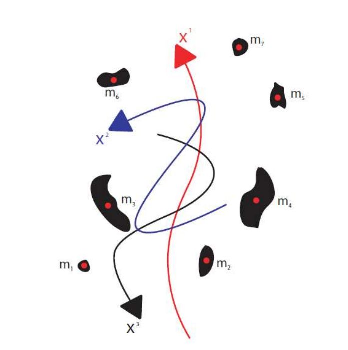

Given $\mathbf{X}^1$:

$\mathbf{M} = [\mathbf{m}_1, \mathbf{m}_2, \mathbf{m}_3, \mathbf{m}_4, \mathbf{m}_5, \mathbf{m}_6, \mathbf{m}_7]$

Given $\mathbf{X}^2$:

$\mathbf{M} = [\mathbf{m}_4, \mathbf{m}_3, \mathbf{m}_2, \mathbf{m}_1, \mathbf{m}_5, \mathbf{m}_7, \mathbf{m}_6]$

Given $\mathbf{X}^3$:

$\mathbf{M} = [\mathbf{m}_6, \mathbf{m}_7, \mathbf{m}_5, \mathbf{m}_4, \mathbf{m}_3, \mathbf{m}_2, \mathbf{m}_1]$

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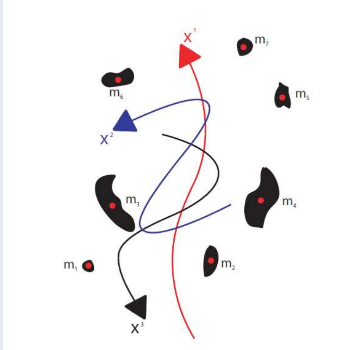

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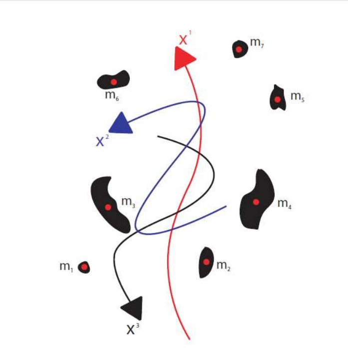
- Estimated map vector depends on vehicle trajectory ???

What's Wrong with Random Vectors?



$$\underbrace{\begin{array}{l}\widehat{M} = [m_1\ m_2\ m_3\ m_4\ m_5\ m_6\ m_7]^T \\ \widehat{M} = [m_4\ m_2\ m_3\ m_1\ m_5\ m_7\ m_6]^T \\ \vdots \\ \widehat{M} = [m_6\ m_7\ m_5\ m_4\ m_3\ m_2\ m_1]^T\end{array}}$$
$$\widehat{\mathcal{M}} = \{m_1\ m_2\ m_3\ m_4\ m_5\ m_6\ m_7\}$$

- RFS makes more sense as order of features *cannot/should not* be significant.

[8] J. Mullane, B.-N. Vo, M. Adams, B.-T. Vo, *A Random-Finite-Set Approach to Bayesian SLAM*, IEEE Transactions on Robotics, Vol. 27, No. 2, pages 268 – 282, April 2011.

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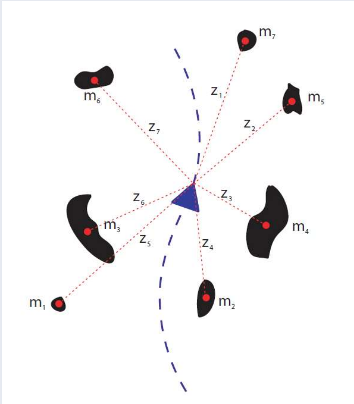


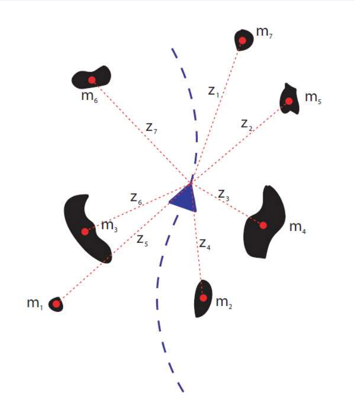
Untangle:

$\mathbf{Z} = [\mathbf{z}_1, \mathbf{z}_2, \mathbf{z}_3, \mathbf{z}_4, \mathbf{z}_5, \mathbf{z}_6, \mathbf{z}_7]$

?

$\mathbf{M} = [\mathbf{m}_1, \mathbf{m}_2, \mathbf{m}_3, \mathbf{m}_4, \mathbf{m}_5, \mathbf{m}_6, \mathbf{m}_7]$

Random Finite Sets Circumvent the Need for Data Association



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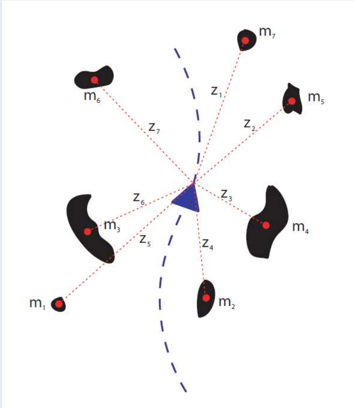

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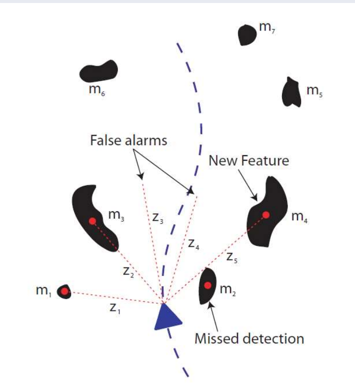
Current vector formulations *require* data association (DA) prior to Bayesian update:

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

RFS approach *circumvents* external DA decisions.

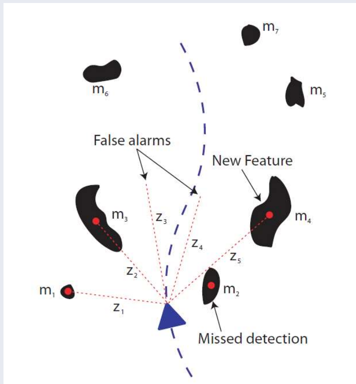
Why? Features & measurements are finite valued sets. No distinct order assumed.

The Mathematics of “Map Management”



How to integrate new map features:

The Mathematics of “Map Management”

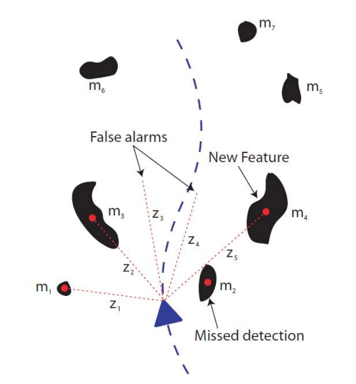


How to integrate new map features:

...with random vectors:

$$\widehat{M}_{k-1} = [m_1 \;\; m_2 \;\; m_3]^T$$
$$\widehat{M}_k \stackrel{?}{=} [m_1 \;\; m_2 \;\; m_3]^T \text{“}+\text{”} [m_4]$$

The Mathematics of “Map Management”



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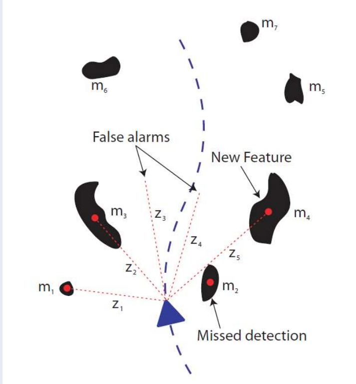
$$\widehat{M}_{k-1} = [m_1 \ m_2 \ m_3]^T$$
$$\widehat{M}_k \overset{?}{=} [m_1 \ m_2 \ m_3]^T \text{``}+\text{''} [m_4]$$

...with random sets:

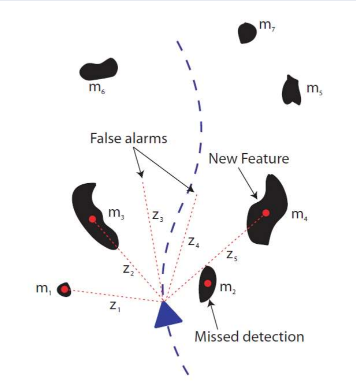
$$\widehat{\mathcal{M}}_{k-1} = \{m_1 \ m_2 \ m_3\}$$
$$\widehat{\mathcal{M}}_k = \{m_1 \ m_2 \ m_3\} \cup \{m_4\}$$

The Mathematics of Missing or Extra Measurements



How to write measurement/observation model:

The Mathematics of Missing or Extra Measurements



How to write measurement/observation model:

...with random vectors:

$$Z_k = h([m_1 \ m_2 \ m_3 \ m_4], X_k) + \text{noise}$$
$$\text{i.e.}: \ [z_1 \ z_2 \ z_3 \ z_4 \ z_5]^T \overset{?}{=} h([m_1 \ m_2 \ m_3 \ m_4], X_k) + \text{noise}$$

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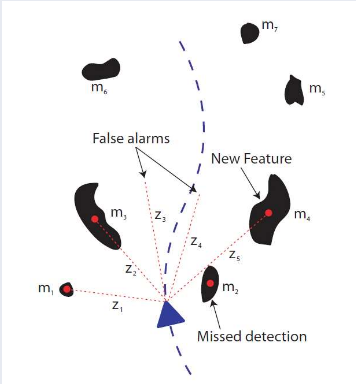

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...with random sets:

$$\mathcal{Z}_k = \bigcup_{m \in \mathcal{M}_k} \mathcal{D}_k(m, X_k) \cup \mathcal{C}_k(X_k)$$

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State-of-art SLAM: Modelling Measurements & Map

$\mathcal{Z}_k \equiv \{\mathbf{z}_k^1, \mathbf{z}_k^2, \ldots, \mathbf{z}_k^{n_k}\}$ Collected measurements/detections random in number, and have no specific order.

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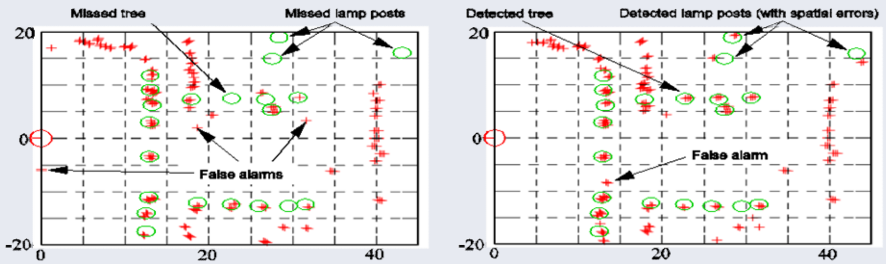

(a) Radar point detections based on an OS-CFAR detector.

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

Hence, at any instant, a sensor can be considered to collect a finite set $\mathcal{Z} = \{z^1, \ldots, z^3\}$ of measurements $z^1, \ldots, z^3$ from a measurement space $\mathcal{Z}_0$ as follows:

$$\begin{array}{lcl} \mathcal{Z} = & \emptyset & \text{(no features detected)} \\ \mathcal{Z} = & \{z^1\} & \text{(one feature } z^1 \text{ detected)} \\ \mathcal{Z} = & \{z^1, z^2\} & \text{(two features } z^1, z^2 \text{ detected)} \\ \vdots & \vdots & \vdots \\ \mathcal{Z} = & \{z^1, \ldots, z^3\} & \text{(3 features } z^1, \ldots, z^3 \text{ detected)} \end{array} \quad (2)$$

RFS SLAM: General Measurement Likelihood

Introduce SLAM state probability of detection: $P_D(\mathbf{x}_k, \mathbf{m})$

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...and likelihood of measurements being clutter: $p\left(\mathcal{Z}_k\right)$

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Introduce SLAM state probability of detection: $P_D(\mathbf{x}_k, \mathbf{m})$

...and likelihood of measurements being clutter: $p\left(\mathcal{Z}_k\right)$

...and assuming multi-Bernoulli distribution:

$$p\left(\mathcal{Z}_k | \mathcal{M}_k, \mathbf{x}_{0:k}\right) = \sum_{\boldsymbol{\theta}} \left(\underbrace{p\left(\mathcal{Z}_k^{\boldsymbol{\theta}} | \mathcal{M}_k^{\boldsymbol{\theta}}, \mathbf{x}_{0,k}, \boldsymbol{\theta}\right)}_{\substack{\text{Spatial measurement} \\ \text{likelihood for state-} \\ \text{measurement pairs} \\ \text{under association } \boldsymbol{\theta}}} \underbrace{\left[\prod_{\mathbf{m} \in \mathcal{M}_k^{\boldsymbol{\theta}}} P_D\left(\mathbf{x}_k, \mathbf{m}\right)\right]}_{\substack{\text{For all associated} \\ \text{state elements:} \\ \text{Product of their} \\ \text{detection probabilities}}} \underbrace{\left[\prod_{\mathbf{m} \in \overline{\mathcal{M}_k^{\boldsymbol{\theta}}}} \left(1 - P_D\left(\mathbf{x}_k, \mathbf{m}\right)\right)\right]}_{\substack{\text{For all unassociated} \\ \text{state elements: Product} \\ \text{of their misdetection} \\ \text{probabilities}}} \underbrace{p_\kappa\left(\overline{\mathcal{Z}_k^{\boldsymbol{\theta}}}\right)}_{\substack{\text{Likelihood} \\ \text{of non-associated} \\ \text{measurements} \\ \text{being clutter}}} \right)$$

SLAM Ideal Detection Conditions

- 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

[10] K. Leung, F. Inostroza, M. Adams, *Relating Random Vector and Random Finite Set Estimation in Navigation, Mapping and Tracking*, IEEE Trans. Signal Processing, Vol. 65, No. 17, Sept. 2017.

Difference Between RFS and Vector State Models

Bayesian Estimation:

Model state as random Vector $\mathbf{X}$:

$$p(\mathbf{X} \mid \mathcal{Z}) = \frac{p(\mathcal{Z} \mid \mathbf{X})\, p(\mathbf{X})}{p(\mathcal{Z})}$$

Change order (permute) elements of $\mathbf{X}$ - different Bayesian estimate.

Model state as random Set $\mathcal{X}$:

$$p(\mathcal{X} \mid \mathcal{Z}) = \frac{p(\mathcal{Z} \mid \mathcal{X})\, p(\mathcal{X})}{p(\mathcal{Z})}$$

Change order (permute) elements of $\mathcal{X}$ - same Bayesian estimate.

SLAM with Random Finite Sets (RFS)

Why use Random Finite Sets (RFS)?

1. Set algebra
2. Implicit data association
3. Allows mathematically consistent definition of error metrics

RFS Solutions:

1. Probability Hypothesis Density (PHD) Filter

[8] J. Mullane, B.-N. Vo, M. Adams, B.-T. Vo, *A Random Finite Set Approach to Bayesian SLAM*, IEEE Trans. Robotics, Vol. 27, No. 2, April 2011.

[11] L. Gao, G. Battistelli, and L. Chisci, "*PHD-SLAM 2.0: Efficient SLAM in the presence of misdetections and clutter*," IEEE Trans. Robotics, 2021.

2. Labelled Multi-Bernoulli (LMB) Filter

[12] H. Deusch, S. Reuter, K. Dietmayer, "*The Labeled Multi-Bernoulli SLAM Filter*", IEEE Signal Proc. Letters, Vol 22, No. 10, Oct. 2015.

[13] D. Moratuwage, M. Adams, F. Inostroza, *δ-Generalized Labeled Multi-Bernoulli Simultaneous Localization and Mapping with an Optimal Kernel-based Particle Filtering Approach*, MDPI Sensors, Vol. 19, Issue 10, May 2019.

3. Joint Vector-Set (JVS)-SLAM solver

RFS - GraphSLAM Solutions with Non-Linear Least Squares Solvers

Joint Vector-Set (JVS)-SLAM Solver:

- Seek the posterior: $p\left(\boldsymbol{x}_{0:k}, \mathcal{M}_k \middle| \mathcal{Z}_{1:k}, \boldsymbol{u}_{0:k}\right)$
- Observation: the map set $\mathcal{M}_k$ and the vector trajectory $\boldsymbol{x}_{0:k}$ are correlated.
- Need a mixed vector-set (hybrid) distribution.

A Joint Vector–Set (JVS)–SLAM Distribution

- Start with a single element set and a vector
- Define the Joint Vector–Set (JVS) Object: $\chi_k = (\mathbf{x}_{0:k}, \mathcal{M})$

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- The following distribution results:

$$\pi(\chi_K) = \begin{cases} (1-r)\pi_0(\mathbf{x}_{0:K}) & \chi_K = (\mathbf{x}_{0:K}, \varnothing), \\ r\pi_1(\mathbf{x}_{0:K}, m) & \chi_K = (\mathbf{x}_{0:K}, \{m\}), \\ 0 & \text{else,} \end{cases}$$

$\pi_0(\mathbf{x}_{0:k})$: Vector distribution on vehicle trajectory, given empty map.

$\pi_1(\mathbf{x}_{0:K}, m)$: Joint dist. on vehicle traj. & map element m tuple, given that map is singleton.

r : existence probability of the map element m.

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Apply Multi-Bernoulli Filter: *Each Bernoulli component has distinct map size & data assoc*.

Weights from JVS-SLAM solver, spatial distribution from g2o.

JVS–SLAM (HGLMB–SLAM) vs g2o Back–End + ML Data Assoc.

Unifying the SLAM Back and Front Ends:
A Bayesian Approach with Random Finite Sets.

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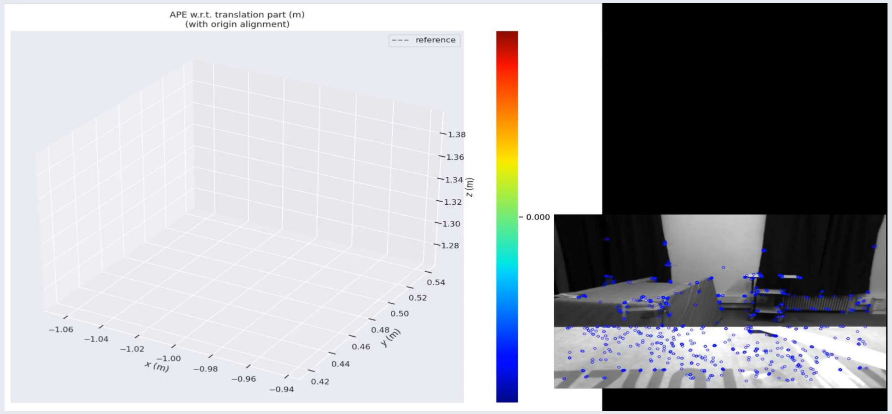
Inostroza F. | HGLMB SLAM

JVS-SLAM vs g2o Back-End + NN & ML Data Assoc. Front-End

Video – stacked.

JVS-SLAM vs ORBSLAM 3 – Challenging EuRoC Dataset



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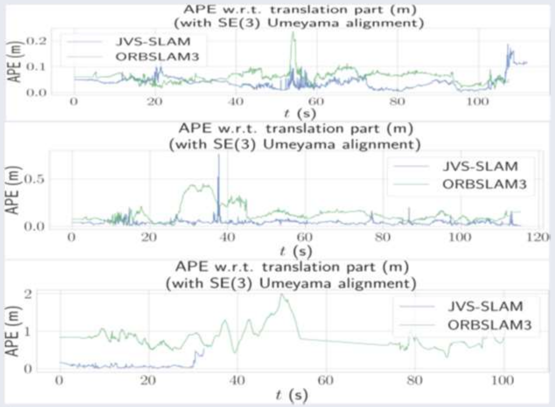

EuRoC Micro Aerial Vehicle, Visual-Inertial dataset.

“EASY”

“MEDIUM”

“DIFFICULT”

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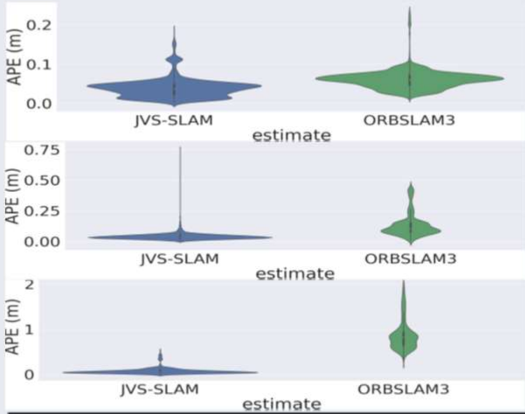

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Presentation Outline

1. Radar-Based SLAM & Multi-Target Tracking.
2. Lessons from Radar – Random Finite Set (RFS) Formulations.
   - Motivation for new Mapping/SLAM concepts.
3. Simultaneous Localisation & Mapping (SLAM) with RFSs.
   - Relation between RFS and RV-SLAM
   - RFS versus Random Vector (RV)-SLAM Results.
4. Future Work in RFS based Mapping/SLAM.

Conclusions

Radar taught us how to reformulate SLAM/MTT!

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State of art RV SLAM methods:

- Deal with detection uncertainty via heuristic methods.
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Conclusions

Radar taught us how to reformulate SLAM/MTT!

State of art RV SLAM methods:

- Deal with detection uncertainty via heuristic methods.
- Apply external (to Bayes/ML estimator) measurement to feature/track association methods. Requires computational approximations.

State of art RFS SLAM methods:

- Intrinsically account for detection & spatial uncertainty.
- Apply Bayes/ML estimation to all measurements/estimated features/targets. Requires computational approximations.

Future Work

1. Probabilistic sensor modelling – improve detection statistics, e.g. occlusions.
2. Incorporate hypothesis tree structure (eg: Hsaio & Kaess).
3. Extended target filtering.

[14] Hsiao M and Kaess M, MH-iSAM2: Multi-hypothesis iSAM using Bayes tree and hypo-tree. In: 2019 International Conference on Robotics and Automation (ICRA). pp. 1274–1280.

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