

week	Date	Lecture (W: 12:05-1:50, 50-N201)
1	29-Jul	Introduction
2	5-Aug	Representing Position & Orientation & State (Frames, Transformation Matrices & Affine Transformations)
3	12-Aug	Robot Kinematics Review (& Ekka Day)
4	19-Aug	Robot Dynamics
5	26-Aug	Robot Sensing: Perception
6	2-Sep	Robot Sensing: Multiple View Geometry
7	9-Sep	Robot Sensing: Feature Detection (as Linear Observers)
8	16-Sep	Probabilistic Robotics: Localization
9	23-Sep	Quiz & Guest Lecture (Tabled) & SLAM
	30-Sep	Study break
10	7-Oct	Motion Planning
11	14-Oct	State-Space Modelling
12	21-Oct	Shaping the Dynamic Response



SLAM! (Better than SMAL!)

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Components of SLAM Localisation Determine pose given a priori map Mapping Generate map when pose is accurately known from auxiliary source. SLAM Define some arbitrary coordinate origin Generate a map from on-board sensors Compute pose from this map Errors in map and in pose estimate are dependent.

















SLAM Convergence

- An observation acts like a displacement to a spring system
 - Effect is greatest in a close neighbourhood
 - Effect on other landmarks diminishes with distance
 - Propagation depends on local stiffness (correlation) properties
- With each new observation the springs become increasingly (and monotonically) stiffer.
- In the limit, a rigid map of landmarks is obtained.
 - A perfect *relative* map of the environment
- The location accuracy of the robot is bounded by
 - The current quality of the map
 - The relative sensor measurement

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Marginalisation:

Removing past poses and obsolete landmarks

• Augmenting with new pose and marginalising the old pose gives the classical SLAM prediction step

$$p(\mathbf{x}_{v_k}, \mathbf{m}_1, \dots, \mathbf{m}_N) = \int p(\mathbf{x}_{v_k}, \mathbf{x}_{v_{k-1}}, \mathbf{m}_1, \dots, \mathbf{m}_N) d\mathbf{x}_{v_{k-1}}$$

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Fusion: Incorporating observation information • Conditional PDF according to observation model $p(\mathbf{z}_{i_k}|\mathbf{x}_k) = \int p(\mathbf{z}_{i_k}|\mathbf{x}_{v_k}, \mathbf{m}_i, \mathbf{r}_k) p(\mathbf{r}_k) d\mathbf{r}_k$ $= \int \delta(\mathbf{z}_{i_k} - \mathbf{h}(\mathbf{x}_{v_k}, \mathbf{m}_i, \mathbf{r}_k)) p(\mathbf{r}_k) d\mathbf{r}_k$ • Bayes update: proportional to product of likelihood and prior $p(\mathbf{x}_k | \mathbf{Z}_{0:k}) = \frac{p(\mathbf{z}_{i_k} = \mathbf{z}_0 | \mathbf{x}_k) p(\mathbf{x}_k | \mathbf{Z}_{0:k-1})}{p(\mathbf{z}_{i_k} = \mathbf{z}_0)}$



EKF SLAM

- The complicated Bayesian equations for augmentation, marginalisation, and fusion have simple and efficient closed form solutions for linear Gaussian systems
- For non-linear systems, just linearise
 - EKF, EIF: Jacobians
 - UKF: use deterministic samples

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Kalman Implementation

- So can we just plug the process and observation models into the standard EKF equations and turn the crank?
- Several additional issues:
 - Structure of the SLAM problem permits more efficient implementation than naïve EKF.

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- Data association.
- Feature initialisation.

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Structure of SLAM • Key property of stochastic SLAM - Largely a *parameter* estimation problem Since the map is stationary ٠ - No process model, no process noise For Gaussian SLAM • - Uncertainty in each landmark reduces monotonically after landmark initialisation - Map converges Examine computational consequences of this structure in next ٠ session. × METR 4202: Robotics 16 September 2015 - 38





New Features

















