# Towards Lifelong Feature-Based Mapping in Semi-Static Environments

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International Conference on Robotics and Automation May 17, 2016





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Our approach: Model feature persistence beliefs



### Main idea: the feature persistence model

We propose the following *feature persistence model* to reason about temporal change in semi-static environments:

$$T \sim p_T(\cdot),$$

$$X_t | T = \begin{cases} 1, & t \leq T, \\ 0, & t > T, \end{cases}$$

$$Y_t | X_t \sim p_{Y_t}(\cdot | X_t; P_M, P_F).$$

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20 40

Feature persistence model

100 120 140 160

3

Time (t)

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#### Key properties:

- Feature abstraction: works with any map representation
- Fully Bayesian: *explicitly models* uncertainty
- Accepts any  $p_T(\cdot)$ : supports a rich modeling framework
- Speed: admits constant-time online inference

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- The persistence filter, an exact, constant-time online inference method for computing persistence beliefs; and
- Methods for designing custom priors to encode a priori knowledge of environmental dynamics.



