Rigorously Bayesian Multitarget Tracking and Localization

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Overview

1. Introduction
2. Methodology
3. Contributions
4. General Conclusion
Overview

1. Introduction
   - Motivation
   - Problem Statement
   - Contributions

2. Methodology

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Motivation

Industrial robots
Motivation

Future robots
Overview

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Problem Statement

Requirements for future robots

- cognitive
- safe
- aware of environment $\Rightarrow$ equipped with sensors
- able to cope with real-world environments
  - uncertainty
  - dynamics
Problem Statement

Requirements for future robots

- cognitive
- safe
- aware of environment ⇒ equipped with sensors
- able to cope with real-world environments
  - uncertainty
  - dynamics

Focus of thesis

Multitarget tracking and localization

What? Tracking targets in the neighborhood of a robot

Why? A necessary feature for future robots

+ other applications: surveillance, animal tracking, ...
Problem Statement

Multitarget tracking and localization (MTTL)

- Tracking
- Multitarget tracking (MTT)
- Multitarget tracking (MTT) and localization
Problem Statement

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Problem Statement

Multitarget tracking and localization (MTTL)

- Tracking
- Multitarget tracking (MTT)
- Multitarget tracking (MTT) and localization
Multitarget tracking and localization (MTTL)

Challenges

- **Data association**: all possible associations \(\Rightarrow\) combinatorial explosion
  - clutter + occlusions + close target interactions
- **Curse of dimensionality**: exponential increase state-space size
- **Unknown and varying** number of targets
- **Online** capabilities
Overview

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Contributions

Goal

Online multitarget tracking and localization (MTTL)

Four contributions to MTTL

- Rigorously Bayesian beam model (Chapter 3)
- Overview and classification of MTTL algorithms (Chapter 4)
- Shape-based online MTTL (Chapter 5)
- Fully Bayesian mixture particle filter (Chapter 6)

Methodology

Rigorously Bayesian Approach
Overview

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   - Rigorously Bayesian Approach
   - Bayesian Networks

3. Contributions

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4. General Conclusion
Rigorously Bayesian Approach

- unknown variables are estimated using fully Bayesian methods
- trade offs and assumptions are made explicit (Bayesian prior)
- uses Bayesian networks to graphically represent models
Rigorously Bayesian Approach

- **Probability theory** provides consistent framework to reason under uncertainty
- **Random variables** are basic building blocks

**Frequentist interpretation**
probabilities represent the outcome of random, repeatable events

**Bayesian interpretation**
probabilities are a *subjective* quantification of uncertainty

↔
Example: throwing a die

**Problem statement:** What is the probability of throwing 5 pips?

→ scientifically:

- random variable $X = \text{outcome of throwing the die}$
- $P(X = 5) =$?
Example: throwing a die

**Frequentist interpretation**: Let’s do some experiments to find out.


*no prior knowledge:*

Since there are no experiments available yet: no information
Rigorously Bayesian Approach

Example: throwing a die

Frequentist interpretation: Let's do some experiments to find out.

throw 1

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Rigorously Bayesian Approach

Example: throwing a die

Frequentist interpretation: Let’s do some experiments to find out.

*throw 2*

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<tr>
<th></th>
<th>1</th>
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Example: throwing a die

**Frequentist interpretation:** Let’s do some experiments to find out.

*throw 3*
Rigorously Bayesian Approach

Example: throwing a die

**Frequentist interpretation:** Let’s do some experiments to find out.

\[ \text{throw} \infty \]

<table>
<thead>
<tr>
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<th>1</th>
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<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
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<td>16%</td>
<td>20%</td>
<td>16%</td>
<td>16%</td>
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</tbody>
</table>
Rigorously Bayesian Approach

Example: throwing a die

**Bayesian interpretation:** Use prior knowledge.

I believe the die is fair

My confidence in this belief is equal to 20 throws

1 2 3 4 5 6

16.6%
Example: throwing a die

**Bayesian interpretation**: Use prior knowledge.

*throw 1*

1 2 3 4 5 6

16.5% 17.3% 16.5%
Example: throwing a die

Bayesian interpretation: Use prior knowledge.

throw 2
Example: throwing a die

Bayesian interpretation: Use prior knowledge.

throw 3
Rigorously Bayesian Approach

Example: throwing a die

**Bayesian interpretation**: Use prior knowledge.

\[ \text{throw} \sim \infty \]

![Image of a die with labels and probabilities]

- 1: 16%
- 2: 16%
- 3: 16%
- 4: 20%
- 5: 16%
- 6: 16%
Rigorously Bayesian Approach

Advantages
- offers unifying framework to reason under uncertainty
- does not need a large number of experiment before reasoning
- encodes domain, expert, and context-specific knowledge in priors
- makes implicit assumptions explicit through priors

Challenges
- increased complexity
  - higher dimension of estimation space
  - probability distributions can be more complex
Rigorously Bayesian Approach

Advantages
- Offers unifying **framework** to reason under uncertainty
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Challenges
- Increased **complexity**
  - Higher dimension of estimation space
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Solution
- Marginalization
- Approximation schemes
Overview

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   - Rigorously Bayesian Approach
   - Bayesian Networks

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Bayesian Networks

Bayesian Networks

Graphical structures for representing the probabilistic relationships among variables and for doing probabilistic inference with those variables.

A Bayesian network consists of:

- **nodes** and **directed edges**
- nodes represent random variables
- edges represent probabilistic relationship: $P(var|parents)$
- **directed acyclic graph**
Bayesian Networks

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Bayesian Networks

A car start problem
Bayesian Networks

A car start problem
Bayesian Networks

A car start problem
Bayesian Networks

A car start problem
Bayesian Networks

A car start problem

The variables and their states (outcomes):

- Fuel level: ok, not ok
- Spark plugs: clean, not clean
- Fuel meter: not empty, empty
- Start: yes, no
Bayesian Networks

A car start problem

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Bayesian Networks

A car start problem

The causal relationships:
- Fuel level $\rightarrow$ Start, fuel meter
- Spark plugs $\rightarrow$ Start

Bayesian networks encode independence relationships and conditional independence relationships $\Rightarrow$ helps in calculations
Bayesian Networks

A car start problem

The conditional probability tables:

- $P(\text{Fuel level}) = (98\%; 2\%)$
- $P(\text{Spark plugs}) = (96\%; 4\%)$
- $P(\text{Fuel meter} \mid \text{Fuel level})$
- $P(\text{Start} \mid \text{Fuel level, Spark plugs})$
Bayesian Networks

A car start problem

The conditional probability tables:

- \( P(\text{Fuel level}) = (98\%; 2\%) \)
- \( P(\text{Spark plugs}) = (96\%; 4\%) \)
- \( P(\text{Fuel meter} \mid \text{Fuel level}) \)
  - Fuel level
    - ok: 99\%; 1\%
    - not ok: 0.2\%, 99.8\%
- \( P(\text{Start} \mid \text{Fuel level, Spark plugs}) \)
Bayesian Networks

A car start problem

The conditional probability tables:

- \( P(\text{Fuel level}) = (98\%; 2\%) \)
- \( P(\text{Spark plugs}) = (96\%; 4\%) \)
- \( P(\text{Fuel meter} \mid \text{Fuel level}) \)
- \( P(\text{Start} \mid \text{Fuel level}, \text{Spark plugs}) \)

<table>
<thead>
<tr>
<th>Spark plugs</th>
<th>ok</th>
<th>not ok</th>
</tr>
</thead>
<tbody>
<tr>
<td>clean</td>
<td>(99%;1%)</td>
<td>(0%;100%)</td>
</tr>
<tr>
<td>not clean</td>
<td>(1%;99%)</td>
<td>(0%;100%)</td>
</tr>
</tbody>
</table>

Fuel level

ok   not ok

Rigorously Bayesian MTTL

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Bayesian Networks

A car start problem

Inference
My car is not starting. ⇒ Why?
observation: Start=no

BN-calculation:
\[
P(\text{Fuel level} \mid \text{Start}=\text{no}) = (70.7\%, 29.3\%)
\]
and
\[
P(\text{Spark plug} \mid \text{Start}=\text{no}) = (41.9\%, 58.1\%)
\]
A car start problem

Inference

My car is not starting although the fuel meter indicates the tank is not empty. ⇒ Why?

- observation: Start=no and Fuel meter=not empty

BN-calculation:

\[ P(\text{Fuel level} \mid \text{Start}=\text{no}, \text{Fuel meter}=\text{not empty}) = (99.9\%, 0.1\%) \]

and

\[ P(\text{Spark plug} \mid \text{Start}=\text{no}, \text{Fuel meter}=\text{not empty}) = (19.6\%, 80.4\%) \]
A Bayesian network is useful for:

- representing knowledge
- discovering underlying assumptions/hypothesis
- algorithms (exact and approximate) available for BN computation

```plaintext
Fuel level → Fuel meter → Start
Spark plugs → Start
```
Overview

3 Contributions

- Rigorously Bayesian Beam Model (RBBM)
- Overview and Classification of MTTL Algorithms
- Shape-based Online MTTL
- Fully Bayesian Mixture Particle Filter

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Contributions

Rigorously Bayesian Beam Model (RBBM)

Range finders:
- sonar or laser
- distance measurement over set of angles
- **ideal** measurement:
  \[ z^* = g(x, m) \]
- **but:**
  - physical noise
  - inaccurate modeling of sensor, environment, or targets

Solution

\[ \Rightarrow \text{probabilistic measurement model} \quad P(Z = z \mid X = x, M = m) \]
Rigorously Bayesian Beam Model (RBBM)

Range finders:
- sonar or laser
- distance measurement over set of angles
- **ideal** measurement: $z^* = g(x, m)$
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Solution
$\Rightarrow$ probabilistic measurement model $P(Z = z \mid X = x, M = m)$
Contributions

Rigorously Bayesian Beam Model (RBBM)

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- sonar or laser
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Solution

⇒ probabilistic measurement model \( P(Z = z \mid X = x, M = m) \)
Rigorously Bayesian Beam Model (RBBM)

Goal

Probabilistic measurement model for a range finder:

- \( P(Z = z \mid X = x, M = m) \)
- adapted to dynamic environments
Rigorously Bayesian Beam Model (RBBM)

Goal

Probabilistic measurement model for a range finder:

\[ P(Z = z \mid X = x, M = m) \]

adapted to dynamic environments
Rigorously Bayesian Beam Model (RBBM)

Approach

- **Introduce** extra state variables $A$ for the positions of unmodeled objects: $P(Z = z \mid X = x, M = m, A = a)$
- **Marginalize** out extra state variables *before* estimation:

$$P(Z = z \mid X = x, M = m) = \int_a P(Z = z \mid X = x, M = m, A = a) \, P(a) \, da$$

Marginalization

**Marginalization** removes the dependency on knowledge of particular outcomes of the variables marginalized, but the dependence on the distributional parameters of these variables remain.
Contributions

Rigorously Bayesian Beam Model (RBBM)

Rigorously Bayesian Beam Model (RBBM)

\[ X: \text{position of mobile robot (sensor)} \]
\[ M: \text{environment} \]
\[ Z: \text{range measurement} \]
\[ N: \text{number of unmodeled objects} \]
\[ X_N: \text{position of unmodeled objects} \]
\[ K: \text{number of occluding objects} \]
\[ X_K: \text{position of occluding objects} \]
\[ Z_{\text{occl}}: \text{ideal occlusion measurement} \]
Rigorously Bayesian Beam Model (RBBM)

- $X$: position of mobile robot (sensor)
- $M$: environment
- $Z$: range measurement
- $N$: number of unmodeled objects
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Rigorously Bayesian Beam Model (RBBM)

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- $Z_{\text{occl}}^*$: ideal occlusion measurement
Rigorously Bayesian Beam Model (RBBM)

Marginalization

- requires all conditional probability distributions
- lots and lots of integrals, . . .
- only **one approximation** needed to obtain analytic measurement model
Rigorously Bayesian Beam Model (RBBM)

Mixture measurement model

\[ P(z \mid x, m) = \pi_1 P_{\text{hit}}(z \mid x, m) + \pi_2 P_{\text{occl}}(z \mid x, m) + \pi_3 P_{\text{rand}}(z \mid x, m) + \pi_4 P_{\text{max}}(z \mid x, m) \]
Rigorously Bayesian Beam Model (RBBM)
Rigorously Bayesian Beam Model (RBBM)

Model parameters

- Sensor noise: $\sigma_m$
- Probability of hit environment: $p'$
- Probability of unexplainable measurement: $\pi_3$
- Probability of sensor failure: $\pi_4$

$\Rightarrow \Theta = [\sigma_m, p', \pi_3, \pi_4]$
Rigorously Bayesian Beam Model (RBBM)

Maximum Likelihood

- $\Theta = \arg\max \log P(Z \mid X, M, \Theta)$
- Expectation-maximization algorithm (EM)
- **overfitting**
- **Result:** point estimate of parameters

Variational Bayesian

- Rigorously Bayesian approach: prior of parameters
- $\Theta = \arg\max \log P(Z \mid X, M, \Theta) P(\Theta)$
- Expectation-maximization like algorithm
- **Result:** probability distribution over parameters
**Rigorously Bayesian Beam Model (RBBM)**

**Experiment 1**: pick and place task in human populated environment

**Experiment 2**: mobile robot in office environment

**Conclusion**

fewer parameters but explains experimental data as well as state-of-the-art
Rigorously Bayesian Beam Model (RBBM)

Conclusion RBBM

- range finder measurement model for **dynamic environments**
- rigorously Bayesian modeling using **Bayesian network**
  - assumptions and parameters revealed
  - physical interpretation of parameters $\Rightarrow$ parameter choice
- to handle complexity due to rigorously Bayesian modeling
  - **marginalization** to reduce estimation space
  - **approximation schemes** to obtain analytical measurement model $+$ for learning
Overview

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3 Contributions
   • Rigorously Bayesian Beam Model (RBBM)
   • Overview and Classification of MTTL Algorithms
   • Shape-based Online MTTL
   • Fully Bayesian Mixture Particle Filter

4 General Conclusion
**Contributions**

- formulates state-of-the-art MTTL algorithms in **unified framework**
- gives **Bayesian network** representation
- lists **assumptions, advantages and disadvantages, advances**
- presents **classification** in tabular format
- presents **decision diagram** to choose MTTL algorithm
Classification and Analysis of MTTL Algorithms

- Modeled Target Interactions: yes → Fixed Number of Targets: no
- Fixed Number of Targets: yes
- Linear Models: yes
- Online: yes
- Multiple and Merged Measurements: yes
- Modeled Target Interactions: no
- Linear Models: no
- Online: no
- Multiple and Merged Measurements: no
- MCMC-PF: yes
- Multiple and Merged Measurements: no
- PMHT: yes
- Merged Measurements: yes
- Maintains Target Identities: yes
- Multiple Measurements: no
- PMHT: no
- Merged Measurements: no
- ?: IPPF
- Explicit Gating: yes
- MC-JPDAF: yes
- SSPF: no
- Linear Models: yes
- Maintains Target Identities: yes
- Multiple Measurements: no
- Merged Measurements: no
- MG-PHD: yes
- Multiple Hypotheses: no
- Multiple Trackers: no
- MTPF: yes
- MHT: no
- SJPDAF: yes
- HPF: no
- HMPF: no
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Shape-based Online MTTL

Goal

- online
- unknown and variable number of targets
- maintain correct identification of targets $\rightarrow$ trajectories
- multiple measurements per target possible
Shape-based Online MTTL

Goal

- online
- unknown and variable number of targets
- maintain correct identification of targets → trajectories
- multiple measurements per target possible
Shape-based Online MTTL

Low level

- laserScanner
- non-environment measurement
- environment measurement
- environment
- low level features

High level
Shape-based Online MTTL

**Low level**
- clusters measurements
- uses high-level target states and shapes
- fast, flexible estimator
- scales well with number of measurements

**High level**
Shape-based Online MTTL

**Low level**
- clusters measurements
- uses high-level target states and shapes
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**High level**
Shape-based Online MTTL

**Low level**
- Laser scanner
- Non-environment measurements
- Environment measurement
- Low level features

**High level**
- Measurements in cluster jointly assigned to target
- Updates target states ($x$) and shapes ($S'$) with individual measurements
- Uses underlying motion model
- Variable number of targets
Shape-based online MTTL

**Low level**
- Variational Bayesian clustering
- Prior info uses outcome of high level
- Expected positions and shapes of clusters encoded in prior
- Automatic relevance detection
Shape-based online MTTL

High level

- (Sequential) joint probability data association filter
- Number of targets estimator

\[ \cdots \rightarrow x_{t-1,n} \rightarrow x_{t,n} \rightarrow x_{t+1,n} \rightarrow \cdots \]

\[ z_{t-1,m} \rightarrow k_{t-1,m} \rightarrow M_{t-1} \rightarrow \Pi_{t-1} \]

\[ z_{t,m} \rightarrow k_{t,m} \rightarrow M_t \rightarrow \Pi_t \]

\[ z_{t+1,m} \rightarrow k_{t+1,m} \rightarrow M_{t+1} \rightarrow \Pi_{t+1} \]

\[ N \]
Shape-based online MTTL

High level

- (Sequential) joint probability data association filter
- Number of targets estimator

\[ \ldots \rightarrow N_{t-1} \rightarrow N_t \rightarrow N_{t+1} \rightarrow \ldots \]

\[ \ldots \rightarrow M_{t-1} \rightarrow M_t \rightarrow M_{t+1} \rightarrow \ldots \]

Low level
Shape-based online MTTL

Tracking of five people using laser scanner
Shape-based online MTTL

Tracking of ants in the process of nest emigration using video
Shape-based online MTTL

Multi-robot manipulation in a human populated environment
Shape-based online MTTL

Conclusions

- Able to detect entering and leaving targets
- Correct identification of targets throughout tracking
- Multiple measurements per target ⇒ no information loss
- rigorously Bayesian modeling using Bayesian networks
  - Prior encodes information on target states and shapes
- To handle complexity due to rigorously Bayesian modeling
  - marginalization to handle data association problem
  - approximation schemes to represent distribution
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4. General Conclusion
Fully Bayesian Mixture Particle Filter

Mixture particle filter

- **IDEA:** use particle filter
- **PROBLEM:** filter focuses on most visible component (sample degeneration)
- **SOLUTION:** use *mixture* of particle filters → one filter for each target
- **METHOD:** ‘maintain mixture step’ needed
Mixture particle filter

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Mixture particle filter

**IDEA:** use particle filter

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**SOLUTION:** use mixture of particle filters

→ one filter for each target

**METHOD:** ‘maintain mixture step’ needed
Contributions

Fully Bayesian Mixture Particle Filter

Problems with state-of-the-art mixture particle filter

- **nearest-neighbor data association** prevents fully Bayesian tracking
- state-of-the-art maintain mixture step relies on **heuristics** (cluster merging, splitting, k-means clustering, . . .)
- *not* suited for target **detection**
Contributions  Fully Bayesian Mixture Particle Filter

Fully Bayesian Mixture Particle Filter

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Fully Bayesian Mixture Particle Filter

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- nearest-neighbor data association prevents fully Bayesian tracking
- state-of-the-art maintain mixture step relies on heuristics (cluster merging, splitting, k-means clustering, ...)
- not suited for target detection
Contributions

- Convert mixture particle filter into **fully Bayesian MTTL** algorithm
  - introduce Bayesian data association
  - remove heuristics in maintain mixture step
  - extend for target localization
Data association

- **Goal:** all measurements have to be applied to the **entire** state space
- **Method:** requires **adapted measurement model** that takes into account measurements originating from other targets (for instance Rigorously Bayesian Beam Model!)
- **Result:** soft-data association using adapted measurement model

\[
\cdots \rightarrow x_{t-1} \rightarrow x_t \rightarrow x_{t+1} \rightarrow \cdots
\]

\[
M_{t-1} \
\downarrow \\
z_{t-1,m}
\]

\[
M_t \
\downarrow \\
z_{t,m}
\]

\[
M_{t+1} \
\downarrow \\
z_{t+1,m}
\]
Contributions

**Fully Bayesian Mixture Particle Filter**

Data association

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- **Method:** requires **adapted measurement model** that takes into account measurements originating from other targets (for instance Rigorously Bayesian Beam Model!)
- **Result:** soft-data association using adapted measurement model

\[
P(z \mid x, m)
\]
Fully Bayesian Mixture Particle Filter

Heuristic-free maintain mixture step

- **Goal:** avoid heuristics during maintain mixture step
- **Method:** use weighted variational Bayesian clustering
- **Result:** Bayesian Weighted Spatial Reclustering (BWSR) → automatic relevance detection
Fully Bayesian Mixture Particle Filter

**Extension to localization**

- **Goal:** enable target localization
- **Method:** hypothesize new target around unexplained measurements (adapted proposal)
- **Result:** Bayesian Weighted Spatial Reclustering → automatic relevance detection

![Diagram](image)
Fully Bayesian Mixture Particle Filter

Tracking of three people using laser scanner
Contributions

- Fully Bayesian mixture particle filter
- Able to detect entering and leaving targets
- **Rigorously Bayesian modeling** using Bayesian network
- To handle complexity due to rigorously Bayesian modeling
  - marginalization to handle data association problem
  - approximation schemes to represent distributions (particles) and in the BWSR

![Diagram of particle filter]
Overview

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General Conclusion

Rigorously Bayesian Approach
- offers unifying framework to reason under uncertainty
- encodes domain, expert, and context-specific knowledge in priors
- makes implicit assumptions explicit through priors
- Challenge of increased complexity tackled by:
  - marginalization
  - approximation schemes

Four contributions to MTTL
- Rigorously Bayesian Beam Model
- Overview and classification of MTTL algorithms
- Shape-based online MTTL
- Fully Bayesian mixture particle filter