Multiple Object Tracking: Course Outline

Dr. Waqas Afzal

December 5, 2022

Outline

1. Tracking
2. Single Object Tracking
3. Multiple Object Tracking
4. Random Finite Sets
5. Multiple Object Tracking Using Conjugate Pairs

Outline

1. Tracking
   - Introduction
   - Bayesian Filtering
   - Motion Modeling
   - Measurement Modeling
   - Kalman Filter: A Bayesian Filtering Example

Outline

1. Tracking
   - Introduction
   - Bayesian Filtering
   - Motion Modeling
   - Measurement Modeling
   - Kalman Filter: A Bayesian Filtering Example

2. Single Object Tracking

Outline

1. Tracking
   - Introduction
   - Bayesian Filtering
   - Motion Modeling
   - Measurement Modeling
   - Kalman Filter: A Bayesian Filtering Example
2. Single Object Tracking
3. Multiple Object Tracking

Outline

1. Tracking
   - Introduction
   - Bayesian Filtering
   - Motion Modeling
   - Measurement Modeling
   - Kalman Filter: A Bayesian Filtering Example
2. Single Object Tracking
3. Multiple Object Tracking
4. Random Finite Sets

Outline

1. Tracking
    - Introduction
    - Bayesian Filtering
    - Motion Modeling
    - Measurement Modeling
    - Kalman Filter: A Bayesian Filtering Example
2. Single Object Tracking
3. Multiple Object Tracking
4. Random Finite Sets

Outline

1. Tracking

Outline

1. Tracking
2. Single Object Tracking
   - Introduction
   - Prediction & Measurement Updates
   - Clutter Modeling
   - Data Association
   - Algorithms
   - Gating

Outline

1. Tracking
2. Single Object Tracking
   - Introduction
   - Prediction & Measurement Updates
   - Clutter Modeling
   - Data Association
   - Algorithms
   - Gating
3. Multiple Object Tracking

Outline

1. Tracking
2. Single Object Tracking
    - Introduction
    - Prediction & Measurement Updates
    - Clutter Modeling
    - Data Association
    - Algorithms
    - Gating
3. Multiple Object Tracking
4. Random Finite Sets

Outline

1. Tracking
2. Single Object Tracking
   - Introduction
   - Prediction & Measurement Updates
   - Clutter Modeling
   - Data Association
   - Algorithms
   - Gating
3. Multiple Object Tracking
4. Random Finite Sets

Introduction

Single Object Tracking (SOT) and Multiple Object Tracking (MOT)

Single Object Tracking (SOT): SOT is a filtering problem. It can be described as the sequential processing of noisy sensor measurements to determine an object's state:

- Position.
- Other properties like kinematics, etc.
- Other attributes related to the detected object like Electronic Support Measures (ESM) data.

Outline

1. Tracking

Outline

1. Tracking
2. Single Object Tracking

Outline

1. Tracking
2. Single Object Tracking
3. Multiple Object Tracking
   - Introduction

Outline

1. Tracking
2. Single Object Tracking
3. Multiple Object Tracking
    - Introduction
4. Random Finite Sets

Outline

1. Tracking
2. Single Object Tracking
3. Multiple Object Tracking
   - Introduction
4. Random Finite Sets
5. Multiple Object Tracking Using Conjugate Pairs

Introduction

Definition

Multiple Object Tracking (MOT): Multiple Object Tracking (MOT) is the sequential processing of noisy sensor measurements to determine

- the number of dynamic objects,
- and each dynamic object's state.

Simply put, MOT, jointly detects object and applies Single Object Tracking (SOT) to each of these objects.

Outline

1. Tracking

Outline

1. Tracking
2. Single Object Tracking

Outline

1. Tracking
2. Single Object Tracking
3. Multiple Object Tracking

Outline

1. Tracking
2. Single Object Tracking
3. Multiple Object Tracking
4. Random Finite Sets
   - Introduction

Outline

1. Tracking
2. Single Object Tracking
3. Multiple Object Tracking
4. Random Finite Sets
   - Introduction
5. Multiple Object Tracking Using Conjugate Pairs

Outline

1. Tracking

Outline

1. Tracking
2. Single Object Tracking

Outline

1. Tracking
2. Single Object Tracking
3. Multiple Object Tracking

Outline

1. Tracking
2. Single Object Tracking
3. Multiple Object Tracking
4. Random Finite Sets

Outline

1. Tracking
2. Single Object Tracking
3. Multiple Object Tracking
4. Random Finite Sets
5. Multiple Object Tracking Using Conjugate Pairs
   - Introduction

Introduction

- Multiple sensors-multiple target tracking scenario.
- Associating tracks from multiple sensors to a target.
- Errors can affect operators ability to analyze formations and consequently, the intent.

Introduction

Challenges in MOT

- The first challenge is detecting objects. Since the number of dynamic objects is unknown, detection needs to be done at each time step.
- The states of the detected objects are also unknown, thus their states need to be estimated at each time step.
- New objects can enter the sensor's range and objects detected in the previous time step can leave the sensor's range.
- Objects can occlude one another leading to missed detections.
- False alarms or missed detections due to inherent sensor noise.
- Data association
    - which detections are from objects detected previously.
    - which detections are from new objects in the sensors range.
    - false detections (clutter).

Introduction

Types of Tracking

1. **Point Object Tracking:** a single detection is returned per object per time step.
2. **Extended Object Tracking:** multiple detections are returned per object per time step.
3. **Group Object Tracking:** multiple resolvable objects are treated as a group per time step.
4. **Tracking with Muli-Path Propagation:** tracking Non Line-of-Sight (NLOS) dynamic objects.
5. **Tracking with Unresolved Measurements:** multiple objects return a single measurement.

Bayesian Filtering

Introduction

- Tracking is basically detection of dynamic objects and estimation of their hidden states in the presence of uncertainty.
- Bayesian filters have been shown to perform well in estimating hidden states in the presence of uncertainty.
- All Bayesian filters successively follow a two step process.
  - **Motion Update (Prediction)**: Use a motion model to predict the state of the objects in the next time-step.
  - **Measurement Update**: Update the object state's distributions using a measurement model based on the measurement obtained in the current time- step.

Bayesian Filtering

Nomenclature

- $\mathbf{x}_k$ is the state vector of an object at time k.
- $\mathbf{z}_k$ is the measurement vector at time k and $\mathbf{z}_{1:\tau} = (\mathbf{z}_1, \mathbf{z}_2, \ldots, \mathbf{z}_\tau)$ is a sequence of measurements upto time τ.
- **Bayesian Filtering Recursion**
  - **Prediction (Chapman-Kolmongorov Equation)**

$$p(\mathbf{x}_k|\mathbf{z}_{1:k-1}) = \int p(\mathbf{x}_k|\mathbf{x}_{k-1})p(\mathbf{x}_{k-1}|\mathbf{z}_{1:k-1})d\mathbf{x}_{k-1} \tag{1}$$

  - **Update (Bayes Rule)**

$$p(\mathbf{x}_k|\mathbf{z}_{1:k}) = \frac{p(\mathbf{z}_k|\mathbf{x}_k)p(\mathbf{x}_k|\mathbf{z}_{1:k-1})}{p(\mathbf{z}_k|\mathbf{z}_{1:k-1})} \tag{2}$$

  - **Predicted Likelihood (Distribution/Probability of Evidence)**

Bayesian Filtering

Nomenclature

Bayes Update:

$$p(\mathbf{x}_k|\mathbf{z}_{1:k}) = \frac{p(\mathbf{z}_k|\mathbf{x}_k)p(\mathbf{x}_k|\mathbf{z}_{1:k-1})}{p(\mathbf{z}_k|\mathbf{z}_{1:k-1})}$$

$$\begin{aligned} p(\mathbf{x}_k|\mathbf{z}_{1:k}) &\rightarrow \text{Posterior.} \\ p(\mathbf{z}_k|\mathbf{x}_k) &\rightarrow \text{Measurement Likelihood.} \\ p(\mathbf{x}_k|\mathbf{z}_{1:k-1}) &\rightarrow \text{Prior.} \\ p(\mathbf{z}_k|\mathbf{z}_{1:k-1}) &\rightarrow \text{Predicted Likelihood.} \end{aligned}$$

Bayesian Filtering

Nomenclature

Bayesian filtering alternatively applies the prediction and measurement updates to update the posterior of the object state at each time step.

$$
\begin{aligned}
\text{Initial:}\quad & p(\mathbf{x}_1) \\
\text{Update:}\quad & p(\mathbf{x}_1|\mathbf{z}_1) \\
\text{Prediction:}\quad & p(\mathbf{x}_2|\mathbf{z}_1) \\
\text{Update:}\quad & p(\mathbf{x}_2|\mathbf{z}_{1:2}) \\
\text{Prediction:}\quad & p(\mathbf{x}_3|\mathbf{z}_{1:2}) \\
\text{Update:}\quad & p(\mathbf{x}_3|\mathbf{z}_{1:3}) \\
\text{Prediction:}\quad & p(\mathbf{x}_4|\mathbf{z}_{1:3}) \\
\text{Update:}\quad & p(\mathbf{x}_4|\mathbf{z}_{1:4})
\end{aligned}
$$