Multi-sensor surveillance and target tracking

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Exposé scientifique de l’équipe TIPIC
**Motivation:** Methods for estimating populations of objects from sensor data are needed for a broad range of applications, such as

- Space situational awareness
- Maritime surveillance
- Analysis of image sequences
- Ballistic missile defence

**Requirements:** Mathematical models and statistical signal processing algorithms.

- Modelling of observation characteristics of sensor data
- Dynamical models for evolution of target populations

**Research objective:** Develop statistical estimators for populations of objects with appropriate representation and level of uncertainty.
Single-target tracking

Bayes filter (Bayes 1763, Chapman 1928, Kolmogorov 1931)

\[ p_k(x_k | z_{1:k}) \xrightarrow{\text{prediction}} p_{k+1|k}(x_{k+1}|k | z_{1:k}) \xrightarrow{\text{data-update}} p_{k+1}(x_{k+1} | z_{1:k+1}) \]

Kalman filter (Swerling / Stratonovich/ Kalman, late 1950s)

Particle filter (Handschin & Mayne, 1966/ N. Gordon, 1993)
Multi-target tracking (Reid, Bar-Shalom 1970s)

The objective in multi-target tracking is to jointly estimate both the number of targets and their states.
Multi-object modelling for detection and tracking

Populations of objects modelled with *point processes*

- Target population;
- Target interactions;
- Target measurements;
- Missed detections;
- False alarms;
- Target appearing/disappearing;
Multi-object modelling (Moyal 1962)

A spatial point process is a probabilistic representation of a random set of objects.
For example:

- 2-dimensional positions of objects in an image from a sensor (i.e. an observation space).

- 3-dimensional positions and velocities of objects in some real-world environment (i.e. a state space).
Multi-object modelling (Moyal 1962)

A spatial point process is a representation of point patterns that accounts for uncertainty in both the number and locations of objects.

<table>
<thead>
<tr>
<th>Number of objects</th>
<th>Cardinality probability</th>
<th>Spatial density</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>$p_0$</td>
<td>$s_0$</td>
</tr>
<tr>
<td>1</td>
<td>$p_1$</td>
<td>$s_1(x_1)$</td>
</tr>
<tr>
<td>2</td>
<td>$p_2$</td>
<td>$s_2(x_1, x_2)$</td>
</tr>
<tr>
<td>3</td>
<td>$p_3$</td>
<td>$s_3(x_1, x_2, x_3)$</td>
</tr>
<tr>
<td>4</td>
<td>$p_4$</td>
<td>$s_4(x_1, x_2, x_3, x_4)$</td>
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<tr>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>n</td>
<td>$p_n$</td>
<td>$s_n(x_1, x_2, x_3, ..., x_n)$</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
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</tr>
</tbody>
</table>
Propagation of population mean (Mahler 2000)

The intensity function of a point process is the average density of points (expected number of points per unit area).

\[ D(x) = \text{density of expected number of points at } x \]

\[ \int_S D(x) \, dx = \text{expected number of points in } S \]
Tracking target clusters (Clark et al. 2013)
Population variance (Clark et al. TSP 2016, 2018)

Modelling global populations allows us to determine population statistics: variance of the number of targets in a region.

“There are roughly $\mu(B)$ targets, give or take $\sim \text{var}(B)$ within $B$”.

$$\text{var}_\Phi(B) = \mu^{(2)}_\Phi(B, B) - \left[\mu^{(1)}_\Phi(B)\right]^2$$

Motivation: Autonomous decision making in surveillance systems.

Complementary with TIPIC

Multi-object modelling and estimation complements strong expertise in TIPIC:
- Estimation with partially-observed Markov models
- Sequential Monte Carlo filtering methods
- Estimation and detection for multi-sensor fusion
Current projects

AFSOR/AFRL/Dstl grant on Autonomous Systems collaboration with UCL (USD450K):
- Develop multi-object information statistics for multi-sensor management
- Large-scale low-complexity multi-target tracking
- Distributed multi-sensor multi-object data fusion

Thales CIFRE project: