University Defence Research Collaboration (UDRC)
Signal Processing in a Networked Battlespace

WP5: Networked enabled sensor management

WP Leader: D. Clark, *Academics:* Y. Petillot, M. Davies

Researcher: E. Delande

Objective:

WP 5.1: Hierarchical sensor management to target tracking (→ WP2, WP3)
- Unify multi-object Bayesian estimation, multi-sensor data fusion, and sensor management;
- Focus on novelty and clarity of proposed solutions.

WP 5.2: Computationally tractable solution (→ WP6)
WP 5.3: Multi-objective sensor management

Multi-target Bayesian estimation

1. How many vehicles? Where are they?

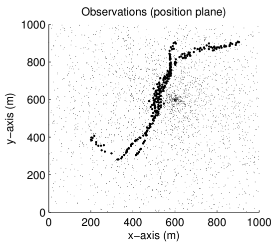
http://www.nollywoodone.com/latest-additions/9009-the-u-s-military-s-real-time-google-street-view-airborne-spy-camera-can-track-an-entire-city-in-1-800mp.html

An individual of the population of interest $\mathcal{X}$ is described, at time $t \geq 0$, by:
- A state $x \in \mathbf{X}_t$ (position, velocity, etc.) if it lies in the scene;
- The "empty state" ψ otherwise.

Key assumptions:
(M1) Individuals are independent;
(M2) Individuals do not reenter the scene.

2. Sensor system (time $t \geq 0$):

- Observations are noisy;
- Individuals in the scene may be miss-detected;
- Presence of spurious observations (*false alarms*).



Range-bearing radar
($\mathrm{SNR} = 9\mathrm{dB}, p_{\mathrm{d}} = 0.65, p_{\mathrm{fa}} = 1^{-03}$)

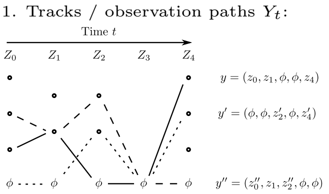
Key assumptions:
(M3) Observations are independent;
(M4) At most one observation per individual.

3. **Problem**: Given the observation sets $Z_0, \ldots, Z_t$, what are the current states of the individuals in $\mathcal{X}$?

Independent stochastic populations

1. Stochastic population of *distinguishable* individuals $\mathfrak{Y}^{\mathrm{d}}_t$:
- Represents the *targets* (i.e. potential individuals) detected *at least once*;
- *Specific* information on individuals available *through detections.*

1.1. Tracks / observation paths Y_t:

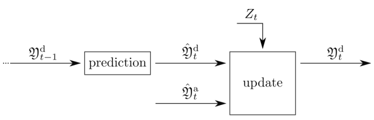


- A target is *characterised* by its observation path y;
- Its state is described by a probability distribution p^y_t on $\mathbf{X}_t \cup \{\psi\}$;
- Probability of *presence* $p^y_t(\mathbf{X}_t)$: is the target currently in the scene?

1.2. Hypotheses H_t:
- An hypothesis $h \subseteq Y_t$ proposes a description of population $\mathcal{X}$;
- Probability $c_t(h)$: how credible is the target configuration proposed by h?
- Probability of *existence* $\alpha^y_t = \sum_{h \in H_t | y \in h} c_t(h)$: how credible is target y?

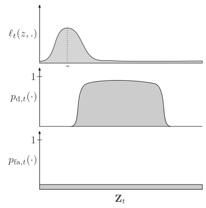
2. Stochastic population of *indistinguishable* individuals $\hat{\mathfrak{Y}}^{\mathrm{a}}_t$:
- Represents targets which have never been detected;
- *Collective* information on population available through *prior information* (cardinality, spatial distribution).

3. ISP filter: (M5) Appearing individuals are always detected when they enter the scene



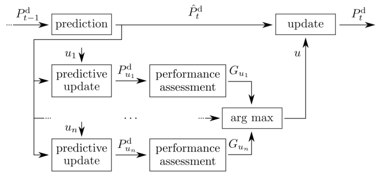
Closed-loop sensor management

1. Sensor modelling
- Likelihood $g_t(z, x)$: how likely is observation z to come from an individual with state x?
- Probability of detection $p_{\mathrm{d},t}(x)$: how likely is an individual with state x to be detected?
- Probability of false alarm $p_{\mathrm{fa},t}(z)$: how likely is the sensor to produce a false alarm with state z?



2. Sensor management problem (time $t \geq 0$)
- A pool of *sensor actions* U_t is available;
- Each sensor action $u \in U_t$ defines an observation profile $(g_u, p_{\mathrm{d},u}, p_{\mathrm{fa},u})$.

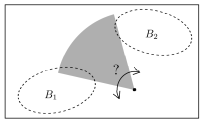
Problem: Which sensor action is likely to be the most informative?



Performance assessment

1. High-order statistics (μ_u, var_u)
- Initially developed for point processes (PHD & CPHD filters, ...);
- Estimate population size within any region $B \subseteq \mathbf{X}_t$;
- Similar to moments for random variables.

Statistics $(\mu_u(B), \mathrm{var}_u(B))$ estimate:
- Target number in B $(\mu_u(B))$,
- with uncertainty $(\mathrm{var}_u(B))$.



Key elements:
- Population-based assessment of sensor actions;
- Can be restricted to any region of the surveillance scene;
- Relatively inexpensive.

2. Information-theoretic gain G_u

Subproblem: If track y is associated to z under sensor action u, what did we learn from p^y_t to $p^{y:z}_u$?

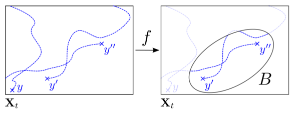
2.1. Individual gain $G^{y:z}_u$ → Rényi divergence from p^y_t to $p^{y:z}_u$

$$G^{y:z}_u = \frac{1}{\alpha - 1} \log \left[\int [p^y_t(x)]^{\alpha} [p^{y:z}_u(x)]^{1-\alpha} \mu(dx) \right] \tag{1}$$

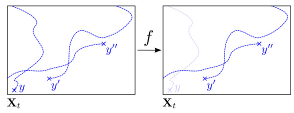
2.2. Total gain G_u → linear combination of all possible individual gains

$$G_u = \sum_{z \in \bar{\mathbf{Z}}_u} \sum_{y \in Y_{t-1}} p^y_t(g_u(z,\cdot)) Q^{y,z}_u G^{y:z}_u + \sum_{z \in \mathbf{Z}_u} p^{\mathrm{a}}_t(g_u(z,\cdot)) Q^{\phi_{t-1},z}_u G^{\mathrm{a}:z}_u, \tag{2}$$

2.3. Region-specific and/or track-specific gain → transformation of gains under well-defined mappings f



Information gain assessed within B only



Information gain assessed for tracks y', y'' only

Key elements:
- Individual-based assessment of sensor actions;
- Can be restricted to any region of the surveillance scene and/or any group of targets;
- Relatively expensive (coefficients Q_u).

Future Work:
1. Design of approximate solutions for an efficient computation of Q_u coefficients;
2. Implementation of performance assessment tools for the ISP filter (Matlab/C);
3. Efficient implementation (explore parallel computing).

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