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

E_WP2: Distributed Multi-sensor Processing

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Abstract

Multi-sensor exploitation is a key capability for developing and enhancing situation awareness. Networks of sensors, however, pose signal and information processing challenges such as maintaining a scalable, robust operation and a flexible structure in a changing environment while complying with their resource limitations.

The main theme of this workpackage is *distributed processing* which overcome these difficulties by removing the need for a single designated processing centre and taking resource constraints such as the availability of communication links, limited communication bandwidth and energy into account in designing strategies.

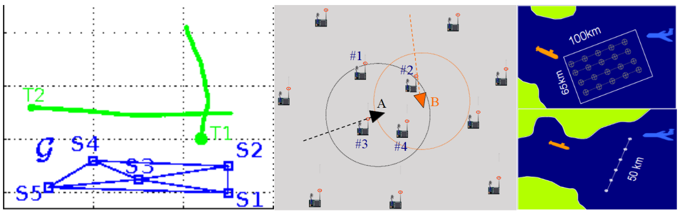
Objectives

The main objective of E_WP2 is to address challenges in detecting and tracking objects with networked sensor platforms of various modalities:

2.1 Distributed Fusion & Registration: Develop scalable and reliable methods for sensor fusion and registration that can be realised by a networked system.

2.2 Distributed Detection: Investigate distributed detection in networks of sensors that are comparably less homogenous in their capabilities.

Technical Challenges



(a) (b) (c)

Figure 1 (a) A distributed fusion network composed of five nodes communicating over the graph $\mathcal{G}$ and tracking two objects. (b) An acoustic sensor network tracking two sources. (c) Networked buoys equipped with sonars.

#26: Sparse, low BW, heterogeneous networks.

#15: (Detection, classification and localisation in) spatially dense sensors with partially correlated acoustic signals.

Sono-buoy challenge: Passive sonar network for tracking underwater targets (Illustrations by Mike Ralph, DSTL).

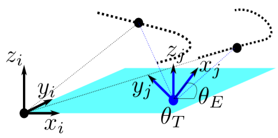
Research Themes

Theoretical frameworks useful in addressing such challenges:

- Approximate statistical inference on probabilistic models including point process and graphical models facilitating distributed operation.
- Distributed maximum likelihood & optimisation methods.
- Accelerated consensus algorithms, diffusion learning.

Recent Progress

<u>Problem</u>: Estimation of sensor registration parameters, e.g., sensor locations and orientations, in *distributed fusion networks* by exploiting non-cooperative targets.



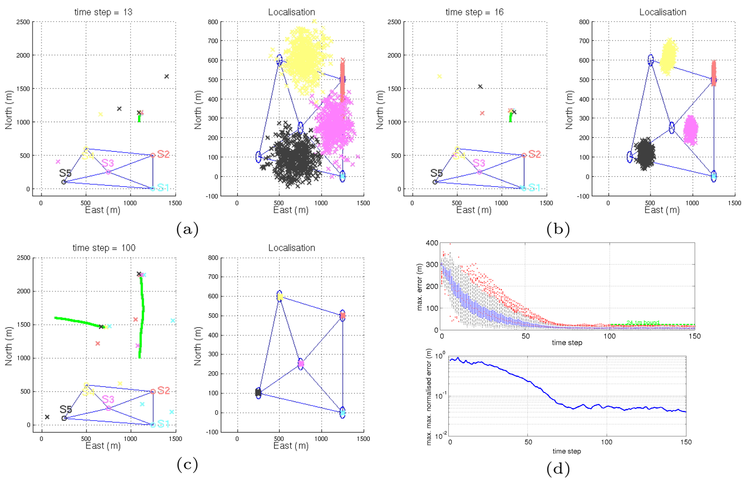
<u>Criticism of the existing approaches:</u>

- The parameter likelihood $l(Z^1_{1:k}, \ldots, Z^N_{1:k}|\theta)$ based on target measurements [1] requires the sensor measurement histories be collected at a designated fusion centre.
- Centralised processing [2] or joint filtering [3], however, is <u>not</u> feasible due to the limitations in communication and computational resources.
- In our distributed fusion paradigm, nodes perform local filtering and communicate the filtering distributions with their immediate neighbours (Fig. 1(a)) to improve upon the myopic accuracy [4].

<u>Our collaborative self-localisation scheme:</u>

- In order to facilitate distributed fusion within self-localisation, we
  1. Approximate the centralised parameter posterior $p(\theta|Z^1_{1:k}, \cdots, Z^N_{1:k})$ with a pairwise Markov Random Field (MRF) $\tilde{p}$ which is Markov with respect to $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ and enables cooperative estimation through (Loopy) Belief Propagation [5]: $\tilde{p}(\theta) \triangleq \prod_{i \in \mathcal{V}} p(\theta_i) \prod_{(i,j)\in\mathcal{E}} l(Z^i_{1:k}, Z^j_{1:k}|\theta_i, \theta_j)$.
  2. Assert a set of conditional independence assumptions through which the local likelihoods (equivalently, the edge potentials of $\tilde{p}$) become computable using the (multi-object) filtering distributions exchanged by the neighbouring nodes for distributed fusion.
- The filtering distributions used in these likelihoods are provided by multi-object filtering algorithms (e.g.,[6]) which are capable of handling noisy measurements from multiple targets with given probability of detection and false alarms.

Example



(a) (b) (c) (d)

Figure 2 Snapshots from a typical run of the proposed scheme with the scenario in Fig. 1(a) demonstrating self-localisation of range-bearing sensors with non-cooperative targets (a)–(c). Convergence properties of the Non-parametric BP [7] with our likelihoods can be seen in the bar plot of the maximum localisation error in the network for 200 Monte Carlo runs (d–top). (d–bottom) The highest ensemble error normalised with the minimum distance between two sensors in the network (430m).

Conlusions and Future Work

- E_WP2 investigates distributed fusion, registration and detection strategies in networked sensing.
- We have recently proposed a cooperative self-localisation scheme for distributed fusion networks which exploits measurement from non-cooperative targets [8].
- Future work includes extensive experimentation for comparison of the performance of the proposed scheme with that of the centralised and naïve likelihoods.
- Additional registration unkowns and models of information sources such as GPS will be introduced into this framework.
- Statistical inference in dynamical graphical models with robust Monte Carlo computational methods will be investigated.

References

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