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

E_WP2: Distributed Multi-sensor Processing

WP Leader: Bernard Mulgrew,
Researchers: Murat Üney, *Daniel* Clark, *John* Thompson, *Neil* Robertson

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.

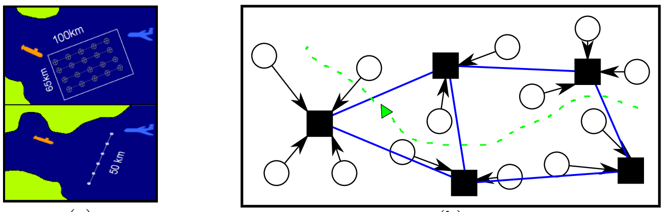
Objectives

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 homogeneous in their capabilities.

Technical Challenges



(a) (b)

Figure 1 (a) Networked buoys equipped with sonars. (b) A hierarchical network structure facilitating robust in-network processing: The first tier forms sensor clusters with processing centres. Decentralised in-network processing among cluster heads takes place in the second tier.

#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).

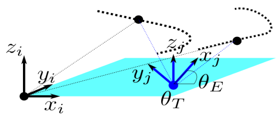
Research Themes

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 (WP2.1):</u> Estimation of sensor registration parameters, e.g., sensor locations and orientations, in *distributed fusion networks* by exploiting non-cooperative targets.



<u>Background:</u>

- The well-known parameter likelihood $l(Z^1_{1:k}, \ldots, Z^N_{1:k}|\theta)$ based on target measurements [1] requires centralised processing or joint filtering [2], which are often <u>not</u> feasible due to the limitations in communication and computational resources.
- In our distributed fusion paradigm, nodes (or cluster heads) perform local filtering and communicate the filtering distributions with their immediate neighbours (Fig. 1(b)) to improve upon the myopic accuracy [3].

<u>Cooperative sensor self-localisation [6]:</u>

- We developed a decentralised scheme which exploits non-cooperative targets.

1. We introduce node-wise separable calibration likelihoods for a pair of sensors which are recursively updated using only the (multi-object) filtering distributions exchanged by the neighbouring nodes for distributed fusion and local measurements.
2. We 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 has our separable likelihoods as edge potentials. $\tilde{p}$ enables cooperative estimation through (Loopy) Belief Propagation [4]: $\tilde{p}(\theta) \triangleq \prod_{i \in \mathcal{V}} p(\theta_i) \prod_{(i,j) \in \mathcal{E}} l(Z^i_{1:k}, Z^j_{1:k}|\theta_i, \theta_j)$.

- Our likelihoods use the first-order moments of the filtering distributions which can be provided by, for example, the filtering algorithms in [5]. This enables us to handle a wide range of uncertainties related to target measurements (e.g., association uncertainties and false alarms) and benefit from the rich source of multi-target information.

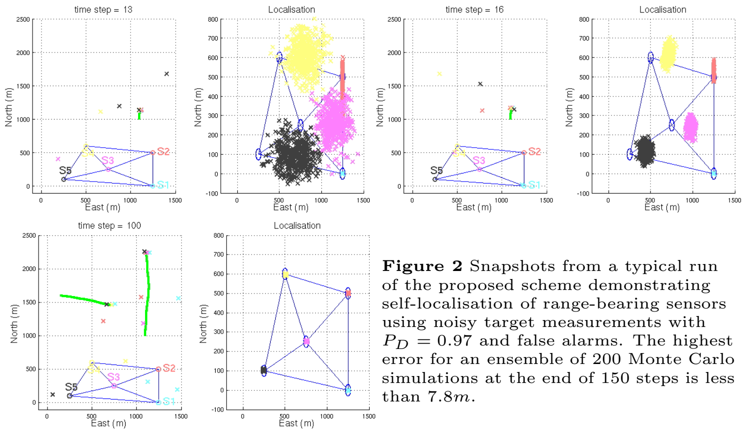
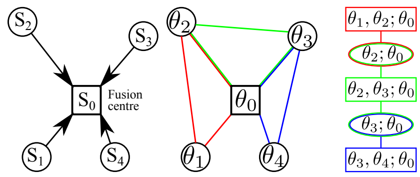


Figure 2 Snapshots from a typical run of the proposed scheme demonstrating self-localisation of range-bearing sensors using noisy target measurements with $P_D = 0.97$ and false alarms. The highest error for an ensemble of 200 Monte Carlo simulations at the end of 150 steps is less than $7.8m$.

<u>Scalable localisation for sensor clusters [7]:</u>

- We consider bearings-only sensor clusters and locating the peripherals with respect to the fusion centre using only the target measurements.
- We propose a solution that scales with the number of sensors, relaxing the computational demand at the fusion centre.



(a) (b) (c)

Figure 3 (a) A sensor cluster which consists of a fusion centre and peripheral sensors. (b) A triangulated Markov Random Field model for the in-cluster localisation problem. (c) Corresponding Junction Tree (JT) over which the individual results for the 3−cliques are combined using the JT estimation algorithm.

Conclusions and Future Work

- E_WP2 investigates scalable fusion, registration and detection strategies for networks of sensor platforms.
- We have recently proposed a cooperative self-localisation scheme for distributed fusion networks which exploits measurements from non-cooperative targets [6].
- Another contribution of E_WP2 is a scalable (centralised) scheme for locating peripheral sensors in bearings-only sensor clusters [7].
- Additional information sources such as received signal strength and GPS will be introduced into these frameworks as well as other registration unkowns.
- Investigation of decentralised multi-sensor detection is scheduled for 2015.

References

[1] O. Cappé, S. J. Godsill, and E. Moulines, “An overview of existing methods and recent advances in sequential monte carlo, *Proceedings of the IEEE*, vol. 95, pp. 899–924, 2007.
[2] N.K. Kantas, S.S. Singh, and A. Doucet, “Distributed maximum likelihood for simultaneous self-localization and tracking in sensor networks,” *IEEE Transactions on Signal Processing*, vol. 60, no. 10, pp. 5038–5047, 2012.
[3] M. Üney, D. E. Clark, and S. Julier, “Distributed Fusion of PHD Filters via Exponential Mixture Densities, *IEEE Journal of Selected Topics in Signal Processing*, vol. 7, no. 3, pp. 521–531, jun 2013.
[4] J. S. Yedidia, W. T. Freeman, and Y. Weiss, “Understanding belief propagation and its generalizations,” Tech. Rep. TR-2001-22, Mitsubishi Electric Research Laboratories, San Francisco, CA, USA, Jan. 2002.
[5] B. Ristic, D. Clark, Ba-Ngu Vo, and Ba-Tuong Vo, “Adaptive target birth intensity for PHD and CPHD filters,” *IEEE Transactions on Aerospace and Electronic Systems*, vol. 48, no. 2, pp. 1656–1668, 2012.
[6] M. Üney, B. Mulgrew, D. Clark, “Cooperative sensor localisation in distributed fusion networks by exploiting non-cooperative targets,” in *Proc. of the IEEE SSPW 2014*, June 2014.
[7] M. Üney, B. Mulgrew, D. Clark, “Target aided online sensor localisation in bearing only clusters,” in *Proc. of the SSPD 2014*, to appear.

This work was supported by the Engineering and Physical Sciences Research Council (EPSRC) and Dstl.