

Data Fusion in Decentralised Sensing Networks.

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1 Introduction

This paper briefly describes the results of a ten year, and still on-going, research program in decentralised sensing systems. This program covers both the theoretical development of data fusion methods appropriate to networks of decentralised sensors and the practical implementation of these in both civilian and military contexts.

Section 2 briefly describes the systems considered and the mathematical methods used for studying decentralised data fusion problem. The methods employed are based on the information-filter formulation of the Kalman filter algorithm and on information-theoretic methods derived from Bayes theorem. Section 3 describes a number of practical implementations of these decentralised data fusion methods and outlines the theoretical tools developed to address such issues as; decentralised communication management, model distribution, decentralised data association and fault detection, sensor control (information gathering, target cuing and hand-off), decentralised picture compilation and map building. Section 4 briefly describes current work toward large-scale 'systems of systems' demonstrations.

2 Decentralised Data Fusion Systems

2.1 What is a Decentralised Data Fusion System ?

A decentralized data fusion system consists of a network of sensor nodes, each with its own processing facility, which together do not require any central fusion or central communication facility. In such a system, fusion occurs locally at each node on the basis of local observations and the information communicated from neighbouring nodes. At no point is there a common place where fusion or global decisions are made.

A decentralised data fusion system is characterised by three constraints:

1. There is no single central fusion center; no one node should be central to the successful operation of the network.
2. There is no common communication facility; nodes cannot broadcast results and communication must be kept on a strictly node-to-node basis.
3. Sensor nodes do not have any global knowledge of sensor network topology; nodes should only know about connections in their own neighbourhood.

Figures 1, 2 and 3 show three possible realisations of a decentralised data fusion system. The key point is that all these systems have no central fusion center (unlike the 'decentralised' systems often described in the literature which are actually typically distributed or hierarchical).

The constraints imposed provide a number of important characteristics for decentralised data fusion systems:

- Eliminating the central fusion center and any common communication facility ensures that the system is **scalable** as there are no limits imposed by centralized computational bottlenecks or lack of communication bandwidth.
- Ensuring that no node is central and that no global knowledge of the network topology is required for fusion means that the system can be made **survivable** to the on-line loss (or addition) of sensing nodes and to dynamic changes in the network structure.
- As all fusion processes must take place locally at each sensor site and no global knowledge of the network is required *a priori*, nodes can be constructed and programmed in a **modular** fashion.

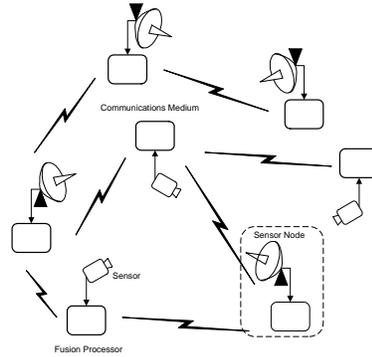


Figure 1: A decentralised data fusion system implemented with a point-to-point communication architecture.

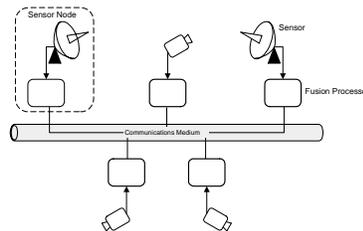


Figure 2: A decentralised data fusion system implemented with a broadcast, fully connected, communication architecture. Technically, a common communication facility violates decentralised data fusion constraints. However a broadcast medium is often a good model of real communication networks.

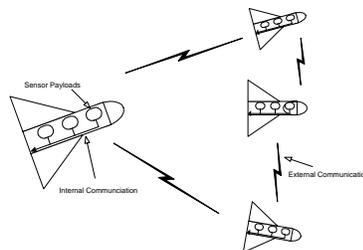


Figure 3: A decentralised data fusion system implemented with a hybrid, broadcast and point-to-point, communication architecture.

2.2 How does a Decentralised Data Fusion System Work ?

The ability to construct a decentralised data fusion architecture clearly depends on whether it is possible to efficiently decentralise existing centralised data fusion algorithms. For most common data fusion algorithms, this turns out to be possible, and indeed many decentralised data fusion algorithms are, surprisingly, *more* efficient, in terms of both computation and communication, than conventional distributed, federated or hierarchical data fusion algorithms.

The initial impetus for decentralised systems was the development of a decentralised form of the Kalman filter algorithm. This is achieved by first recasting the usual Kalman filter state estimation problem in information form. Briefly, consider a state $\mathbf{x}(k)$ with discrete-time index k , a sequence of observations $\mathbf{Z}^k = \{\mathbf{z}(1), \dots, \mathbf{z}(k)\}$, the estimate of this state (conditional mean) $\hat{\mathbf{x}}(i | j) = \mathbb{E}\{\mathbf{x}(i) | \mathbf{Z}^j\}$ together with estimate covariance $\mathbf{P}(i | j) = \mathbb{E}\{\tilde{\mathbf{x}}(i | j)\tilde{\mathbf{x}}^T(i | j) | \mathbf{Z}^j\}$. The information form of the Kalman filter is obtained by re-writing the state estimate and covariance in terms of two new variables

$$\hat{\mathbf{y}}(i | j) \triangleq \mathbf{P}^{-1}(i | j)\hat{\mathbf{x}}(i | j), \quad \mathbf{Y}(i | j) \triangleq \mathbf{P}^{-1}(i | j), \quad (1)$$

and, assuming observations in the form

$$\mathbf{z}(k) = \mathbf{H}(k)\mathbf{x}(k) + \mathbf{v}(k) \quad (2)$$

with $\mathbb{E}\{\mathbf{v}(i)\mathbf{v}^T(j)\} = \delta_{ij}\mathbf{R}(i)$, the information associated with an observation may be written in the form

$$\mathbf{i}(k) \triangleq \mathbf{H}^T(k)\mathbf{R}^{-1}(k)\mathbf{z}(k), \quad \mathbf{I}(k) \triangleq \mathbf{H}^T(k)\mathbf{R}^{-1}(k)\mathbf{H}(k) \quad (3)$$

With these definitions, the update stage of the Kalman filter becomes

$$\hat{\mathbf{y}}(k | k) = \hat{\mathbf{y}}(k | k - 1) + \mathbf{i}(k), \quad (4)$$

$$\mathbf{Y}(k | k) = \mathbf{Y}(k | k - 1) + \mathbf{I}(k). \quad (5)$$

This simple update form comes at the cost of complexity in the prediction stage which is dual to the update stage for the conventional Kalman filter [1].

The information form of the Kalman filter, while widely known, is not commonly used because the update terms are of dimension the state, whereas in the distributed Kalman filter updates are of dimension the observation. For single sensor estimation problems, this argues for the use of the Kalman filter over the information filter. However, in multiple sensor problems, the opposite is true. The reason is that with multiple sensor observations

$$\mathbf{z}_i(k) = \mathbf{H}_i(k)\mathbf{x}(k) + \mathbf{v}_i(k), \quad i = 1, \dots, N$$

the estimate can not be constructed from a simple linear combination of contributions from individual sensors

$$\hat{\mathbf{x}}(k | k) \neq \hat{\mathbf{x}}(k | k - 1) + \sum_{i=1}^N \mathbf{W}_i(k) [\mathbf{z}_i(k) - \mathbf{H}_i(k)\hat{\mathbf{x}}(k | k - 1)],$$

(with $\mathbf{W}_i(k)$ independent gain matrices) as the innovation generated from each sensor is correlated because they share common information through the prediction $\hat{\mathbf{x}}(k | k - 1)$. However, in information form, estimates can be constructed from linear combinations of observation information

$$\hat{\mathbf{y}}(k | k) = \hat{\mathbf{y}}(k | k - 1) + \sum_{i=1}^N \mathbf{i}_i(k),$$

as the information terms $\mathbf{i}_i(k)$ from each sensor are uncorrelated. Once the update equations have been written in this simple additive form, it is straight-forward to distribute the data fusion problem (unlike for a Kalman filter); each sensor node simply generates the information terms $\mathbf{i}_i(k)$, and these are summed at the fusion center to produce a global information estimate.

It is straight-forward to extend the same methods to general data fusion problems defined through a series of conditional probabilities. In essence this is because the information filter is no more than a log-likelihood form of Bayes Theorem (see [4] and [5] for a detailed exposition).

2.3 Operation of Sensor Nodes and Communication Channels

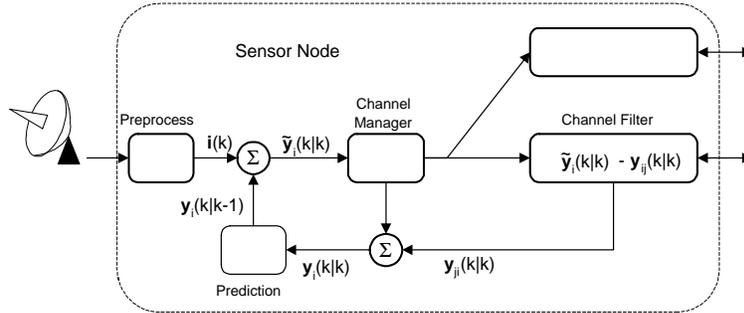


Figure 4: Algorithmic structure of a decentralised sensing node.

To decentralise the information filter all that is necessary is to replicate the central fusion algorithm (summation) at each sensor node and simplify the result. This yields a surprisingly simple nodal fusion algorithm. The algorithm is described graphically in Figure 4 for a typical sensor node, i , in a decentralised data fusion system. The node generates information measures $\hat{\mathbf{y}}_i(k | k)$ at a time k given observations made locally and information communicated to the node up to time k . The node implements a local prediction stage to produce information measure predictions $\hat{\mathbf{y}}_i(k | k - 1)$ at time k given all local and communicated data up to time $k - 1$ (this prediction stage is often the same on each node and may, for example, correspond to the path predictions of a number of common targets). At this time, local observations produce local information measures $\mathbf{i}(k)$ on the basis of local observations. The prediction and local information measures are combined, by simple addition, into a total local information measure $\tilde{\mathbf{y}}_i(k | k)$ at time k . This measure is handed down to the communication channels for subsequent communication to other nodes in the decentralised network. Incoming information from other nodes $\hat{\mathbf{y}}_{ji}(k | k)$ is extracted from appropriate channels and is assimilated with the total local information by simple addition. The result of this fusion is a locally available global information measure $\hat{\mathbf{y}}_i(k | k)$. The algorithm then repeats recursively.

The communication channels exploit the associativity property of information measures. The channels take the total local information $\tilde{\mathbf{y}}_i(k | k)$ and subtract out all information that has previously been communicated down the channel, $\hat{\mathbf{y}}_{ij}(k | k)$, thus transmitting only new information obtained by node i since the last communication. Intuitively, communicated data from node i thus consists only of information not previously transmitted to a node j ; because common data has already been removed from the communication, node j can simply assimilate incoming information measures by addition. As these channels essentially act as information assimilation processes, they are usually referred to as channel filters

Channel filters have two important characteristics:

1. Incoming data from remote sensor nodes is assimilated by the local sensor node *before* being communicated on to subsequent nodes. Therefore, no matter the number of incoming messages, there is only a single outgoing message to each node. Consequently, as the sensor network grows in size, the

amount of information sent down any one channel remains constant and the system as a whole can scale indefinitely.

2. A channel filter compares what has been previously communicated with the total local information at the node. Thus, if the operation of the channel is suspended, the filter simply accumulates information in an additive fashion. When the channel is re-opened, the total accumulated information in the channel is communicated in one single message. The consequences of this are many-fold; burst transmission of accumulate data can be employed to substantially reduce communication bandwidth requirements (and indeed be used to manage communications); if a node is disconnected from the communications network, it can be re-introduced and information synchronised in one step (the same applies to new nodes entering the system, dynamic network changes and signal jamming).

3 Decentralised Data Fusion Algorithms

This section provides a brief description of the many decentralised data fusion algorithms and systems developed and focuses on some current key research issues.

3.1 The Decentralised Kalman Filter

Work on decentralised systems began in 1989 as part of the ESPRIT project SKIDS. In the SKIDS project, a fully decentralised surveillance system was implemented using four cameras and a Transputer based architecture. The network was a fully-connected point-to-point topology. The system was capable of tracking multiple targets (humans and robots) and addressed such issues as decentralised data association and decentralised identification. The algorithms are described in detail in [9, 8]. The SKIDS demonstrator, which continued to be refined and operated for almost 10 years, laid the basis for all subsequent work on decentralised data fusion.

3.2 Communication in Decentralised Systems

An essential limitation with the original decentralized Kalman filter algorithm is that it requires the sensor network to be fully connected so ultimately limiting the size of any realisable decentralized sensing system. The need for fully connectedness is a consequence of the assumption that common information between two neighbouring sites is simply the prior information they share.

This observation led to an analysis of information flow in decentralised sensing networks. By introduction of an additional filter associated with each communication link, it was shown that tree connected network topologies can also be supported by the decentralized Kalman filter algorithm. This is described in detail in [4]. Channel filters, as they became known, also address a number of key issues in data asynchronicity, communications management and network reliability. It was also shown that, within the constraints imposed by the definition of a decentralized sensing network, it is not in general possible to construct a set of filters which can provide consistent estimates across an arbitrary network topology. To overcome this, decentralized routing algorithms were developed to enable construction of tree connected networks from networks of arbitrary topology [10, 11]. Many of these ideas were developed on a large-scale demonstrator as part of the ISSS project. This demonstrator consisted of a model process control system consisting of over 200 sensors linked to over thirty purpose designed decentralized processing sites. The ISSS demonstrator allowed on-line network reconfiguration and software imposed communication bandwidth limitations. The demonstrator was designed to show scalability of decentralised data fusion algorithms to large numbers of sensors.

Further work on communications management has also been undertaken at BAE Systems [3]. This work builds on the idea of a channel filter and other work on information modeling [5] to manage communication between sensing platforms. The work is developed in a military context.

3.3 Model Distribution and Control

Various studies of both model distribution and control issues have been undertaken (see [2, 7, 6] for example). Unsurprisingly, the two problems are coupled and dual to the estimation problem. The most interesting theoretical contribution of this work was in the geometric interpretation of information and the consequent explanation as to why information measures provide efficient decentralised algorithms.

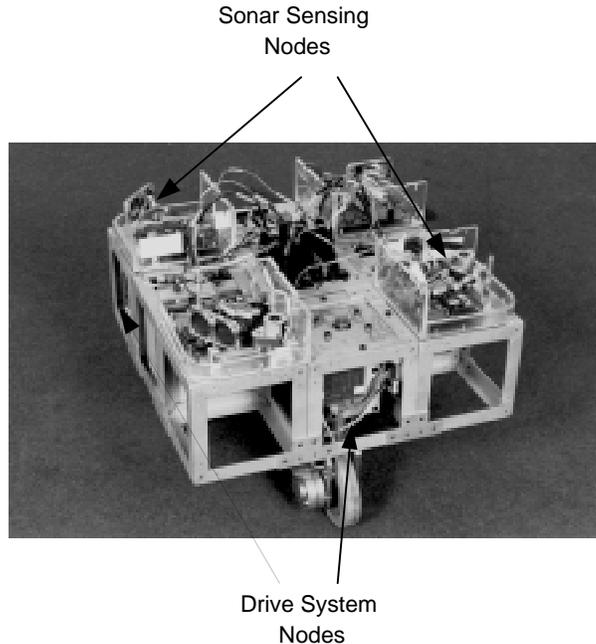


Figure 5: The OxNav Vehicle; a fully modular fully decentralised navigation and control system

These ideas on control were implemented in the OxNav project aimed at demonstrating fully decentralised and modular mobile robot navigation and control. This was a particularly challenging project combining almost all aspects of the theory in a single demonstration system and requiring the physical realization of a mechanical and electrically modular system, and demonstrates more clearly than any other application the potential advantages to be gained from a decentralized approach to systems design (see Figure 5). The Oxnav project also served as a major test-bed for problems in sensor management and decentralised navigation [5].

4 Network-Centric Data Fusion and Control

An obvious application of decentralised data fusion methods is in a military context. We are currently engaged in a project (ANSER) with BAE Systems to demonstrate fully decentralised and modular picture compilation and terrain navigation on single and multiple flight platforms (UAVs). In turn, this will be used to demonstrate, in a highly relevant form to BA Systems operating divisions, how decentralised systems architectures result in; modular packaging of sensor and data fusion algorithms, scalability and on-line

flexibility to addition of single and multiple sensors and flight systems, and robustness and fault tolerance to failure in sensors, systems and platforms.

4.1 Flight Demonstrations

Fundamentally, ANSER is a demonstration project: The objective is to demonstrate functionality of decentralised data fusion theory and algorithms developed over the past 10 years in a form which is of direct relevance to BA Systems business units.



Figure 6: A UAV of the type developed for the ANSER project.

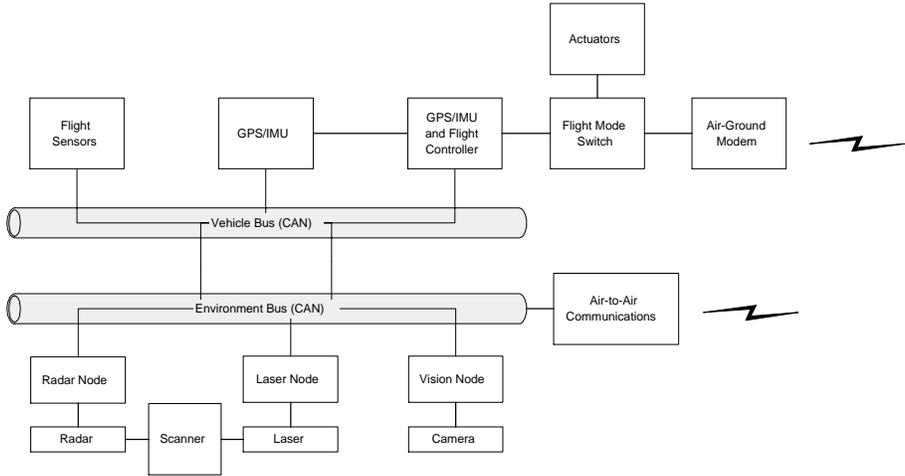


Figure 7: Functional architecture for the UAV. The internal structure provides a CAN bus for vehicle functions (flight critical), and a CAN bus for payload and map information. Each payload is fully modular and interchangeable.

The ANSER project calls for the simultaneous deployment of up to four UAVs in decentralised configuration (see Figures 6 and 7). Four platforms are the minimum allowing demonstration of non-trivial decentralised communication policies. Each UAV is equipped with inertial, GPS and flight data sensors. Each UAV is also equipped with two payload sensors. The first payload sensor is always a passive vision system. The second payload is chosen from either a laser or a mm-wave radar. Both the laser and the radar

are mechanically scanned using a common scanner design. The UAVs are flown at the ACFR flight test facilities at Marulin, 175Km south of Sydney.

The UAVs use the payloads to perform two primary functions:

1. Picture compilation: The detection and tracking of multiple ground targets given known locations (derived from GPS/IMU) for the flight platforms.
2. Simultaneous localisation and map-building (SLAM): The detection and tracking of multiple terrain features together with the simultaneous use of these in estimation of platform location, without independent knowledge of platform location (no GPS).

Each function is developed and demonstrated in fully decentralised and modular form; across payloads on any one flight platform and across multiple payloads on multiple flight platforms.

The scenarios to be flown are aimed at demonstration of the key elements of the decentralised data fusion method. The scenarios can be broken down in to four main groups:

1. Single platform picture compilation: A single platform will be flown with multiple payloads in picture compilation mode. Demonstrations include the modular exchange of payloads (modularity, interoperability), and the in-flight failure and reconfiguration of payloads (survivability and flexibility).
2. Single platform SLAM: A single platform will be flown with multiple payloads in SLAM mode. Demonstrations include flight proving the SLAM method, generation of terrain maps from decentralised payloads, with the same modularity and payload reconfiguration abilities as are demonstrated for picture compilation functions.
3. Multiple platform picture compilation: Multiple flight platforms will be flown with multiple payloads in picture compilation mode. Demonstrations will include the extension of function from one to four platforms (scalability), the transparent use of sensors on one platform by assimilation processes on other platforms (modularity, interoperability), reconfiguration of sensing due to failure of individual payloads, and task reconfiguration due to failure of complete flight platforms (survivability and flexibility).
4. Multiple platform SLAM: Multiple flight platforms will be flown in SLAM mode. Demonstrations will include the ability to share terrain maps between payloads on different flight platforms, to fuse maps from geographically separated payloads, and to demonstrate scalability and robustness of decentralised SLAM methods.

The scenarios form a logical progression for the implementation of the theory and demonstration of algorithms.

4.2 On-Going Research

The ANSER project is focused on demonstration of existing theory. However, the complexity of the demonstrator still requires research in three main areas:

1. The extension of theory and methods to airborne scenarios: There is a necessary process of mapping a general theory and set of methods to this specific, and demanding, application. Most previous work undertaken in decentralised methods has been done on ground-based sensors or land vehicles. An air scenario has more degrees of freedom, faster data rates, and larger demands on processing and communication management.

2. The development of sensing, terrain data acquisition, and terrain or target representation methods: The development and packaging of payload sensors for airborne application has been a significant issue; particularly weight, volume and data acquisition speed. The extraction of appropriate terrain features for picture compilation and SLAM, the modeling and communication of these between different payloads has also been an area of significant study.
3. The development of decentralised and information-theoretic SLAM methods: One significant theoretical advance made in this project is the development of a decentralised formulation of the map building and SLAM problem. This has required the re-formulation of map building equations in information-theoretic form and the study of how maps from different platforms can be exchanged and assimilated.

ANSER has also provoked a number of new research areas, beyond the scope of the current project, but of considerable future value in decentralised systems. This includes the study of ‘Systems of Systems’, and decentralised control.

Acknowledgments

The work described in this paper is based on substantial contributions from many previous and current Ph.D. students; Bobby Rao, Stewart Grime, Tim Berg, James Manyika, Simukai Utete, Tom Burke, Arthur Mutambara, Peter Ho, Mariano Fernandez, and Eric Nettleton. Personnel from BAE Systems have also made major contributions; Phil Greenway and Rob Deaves in particular. Substantial and continual financial support from BAE Systems is also gratefully acknowledged.

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