Distributed Sensor Networks—Introduction to the Special Section

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Guest Editors

I. Introduction

Currently, detection and tracking systems use a large number of different types of sensors. Because of the relatively low cost of sensors, many duplicate sensors of the same type are used to insure increased fault tolerance. The common practice is to assign each sensor of sensor cluster to handle one specific task. For example, while tracking multiple targets, one sensor cluster is assigned to track one target only and any information it may collect about other targets is not utilized.

Thus, there is a great deal of interest in integrating all the sensors so that the information can be effectively utilized. The sophisticated demands made on the tracking and surveillance systems have generated a great deal of interest in developing new architectures that allow for the fusion of the information in the different sensors. For instance, it should be possible to combine the information given by infrared sensors with that given by microwave radars. Any such integration of sensors implies the availability of communication networks that allow for the transfer of information between sensors.

More specifically, the design of spatially distributed target detection and tracking systems involves the integration of solutions obtained by solving subproblems in data-association and fusion, hypothesis testing, effective computational strategies, etc. We envision a decentralized and loosely coupled collection of sensors and a cooperative resolution of the overall problem using the solutions of the subproblems available at local sensors. No single sensor or sensor cluster has the information to solve the entire problem. The common idea of setting up a global processor that receives all the information from the sensors, solves the entire problem, and sends the relevant parts of the solution to the sensors is really not practicable. Both data collection and control have to be logically and geographically distributed necessitating the sharing of information and the use of cooperative problem solving approaches.

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II. What Is a Distributed Sensor Network?

A distributed sensor network (DSN) can be defined as a set of spatially scattered intelligent sensors designed to obtain measurements from the environment, abstract relevant information from the data gathered, and to derive appropriate inferences from the information gained. Distributed sensor networks depend on multiple processors to simultaneously gather and process information from many sources. Interest in these systems stems from a realization of the limitations imposed by relying on a single source of information to make decisions.

Currently, there has been an increasing interest in the development of DSNs for the process of information gathering. Availability of new technology makes these networks economically feasible. The increased complexity of today's information gathering tasks has created a demand for such networks. These tasks are usually time-critical and rely on the reliable delivery of accurate information. Thus, the search for efficient, fault-tolerant architectures for DSNs has become an important research area in computer science.

III. Requirements of Distributed Sensor Networks

A DSN is basically a system of connected, cooperating, generally diverse sensors that are spatially dispersed. *The major task of a DSN* is to process data, possible noise corrupted, acquired by the various sensors and to integrate it, reduce the uncertainty in it, and produce abstract interpretations of it. Three important facts emerge from such a framework:

1) the network must have intelligence at each node,
2) it must accommodate diverse sensors, and
3) its performance must not degrade because of spatial distribution.

Distributed sensor networks are assumed to function under the following conditions:

1) Each sensor in the ensemble can see some but not all of the low-level activities performed by the sensor network as a whole.
2) Data is perishable, in the sense that information value depends critically upon the time required to acquire and process it.
3) There should be limited communication among the sensor processors, so that a communication-computation trade-off can be made.

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4) There should be sufficient information in the system to overcome certain adverse conditions (e.g., node and link failures) and still arrive at a solution in its specific problem domain.

The successful integration of multiple, diverse sensors into a useful sensor network requires the following.

1) The development of methods to abstractly represent information gained from sensors so that this information may easily be integrated.
2) The development of methods to deal with possible differences in points of view on frames of reference between multiple sensors.
3) The development of methods to model sensor signals so that the degree of uncertainty is reduced.

A. Communication in DSNs

In a typical DSN, each node needs to fuse the local information with the data collected by the other nodes so that an updated assessment is obtained. Current research involves fusion based on a multiple hypothesis approach. Maintaining consistency and eliminating redundancy are two important considerations. The problem of determining what should be communicated is more important than how this communication is to be effected. An analysis of this problem yields the following classes of information as likely candidates for being communicated: information about the DSN, information about the state of the world, hypothesis, conjectures and special requests for specific actions. It is easy to see that different classes of information warrant different degrees of reliability and urgency. Further details regarding information fusion in DSNs may be found in [10]–[16.]

IV. Technology Needed

Very little basic research has been done on the fundamental mathematical problems that need to be solved in order to provide a systematic approach to DSN system design. Issues of major interest include optimal distribution of sensors, tradeoffs between communication bandwidth and storage and communication, and maximization of system reliability and flexibility. There are also a number of problems pertaining to communications that need to be resolved e.g., problem of collecting data from a large number of nodes to a specific node. Two related problems are congestion at the collecting point and redundancy in the data obtained from the different nodes.

Current areas of research would include the following topics (but not be limited)

1) A new robust spatial integration model from descriptions of sensors must be developed. This includes the problem of fault-tolerant integration of information from multiple sensors, mapping and modeling the environment space and task level complexity issues of the computational model. Techniques of abstracting data from the environment space on to the information space must be explored for various integration models. For details see [3].
2) A new theory of complexity of processes for sensor integration in distributed environments must be developed. The problems of designing an optimal network and detecting multiple objects has been shown to be computationally intractable. The literature does have some approximate algorithms that may be employed for practical applications. It has been shown that the detection time without preprocessing is at most quadratic for sequential algorithms. What is needed is further work based on these foundations for the computational aspects of more complex detection systems not only in terms of algorithms for detection but also for system synthesis.
3) Distributed image reconstruction procedures must be developed for displaying multiple source locations as an energy intensity map.
4) Distributed state estimation algorithms for defense and strategic applications must be developed (e.g., low altitude surveillance, multiple target tracking in a dense threat environment, etc.). For details see [4].
5) A distributed operating system kernel for efficient synthesis must be developed.

V. Overview of the Papers

In this Special Section, we present a discussion of all the papers in the following categories: architectures, algorithms and complexity issues; statistical estimation and hypothesis testing, and artificial intelligence and neural network based sensor fusion methodologies.

A. Architectures, Algorithms, and Complexity Issues

The search for computationally efficient architectures that are suitable for DSNs has spawned an increasingly important research area. The first five papers of this section deal with the architecture, functional characterization, and the corresponding algorithms in a distributed network environment. The first paper, "Information Integration and Synchronization in Distributed Sensor Networks," by D. N. Jayasimha, S. S. Iyengar and R. L. Kashyap focuses on the computational (architectural, algorithmic, and synchronization) issues related to competitive information integration in a DSN. An information integration algorithm, linear in the number of nodes of the network, is presented. Additional advantages of the algorithm include a low message cost and a low distributed computation cost.

The second paper, "Optimization of Detection Networks," by Z. B. Tang, K. R. Pattipati and D. L. Kleinman considers the distributed binary detection problem with binary communications where the nodes are arranged in a series configuration. The authors present a computationally efficient algorithm based on the min-H method to solve for the optimal decision strategy. Two suboptimal decision rules that can be implemented are proposed and investigated. The third paper, "Topological Analysis of Multiple Satellite Networks," by C. M. Barnhart and R. E. Zeimer presents a method for evaluating the topological quality of a multiple-node satellite communications network based on network survivability and throughput. The authors also present an algorithm for identifying the k shortest paths between a pair of nodes.

The fourth paper, "Computational Complexity Issues in Synthesis of Simple Distributed Detection Networks," by N. S. V. Rao discusses the algorithmic issues of simple object detection problems in the context of a system of finite sensors. Two versions of the problem, forward detection and backward detection, are considered. The author presents both sequential and parallel algorithms and shows that the problem of detecting multiple objects is computationally intractable. The fifth paper, "Functional Characterization of Sensor Integration in Distributed Sensor Networks," by L. Prasad, S. S. Iyengar, R. L. Kashyap and R. N. Madan presents a scheme for narrowing the width of the sensor output in a specific failure model and gives it a functional representation. The authors propose a model that provides a test bed for a general framework that addresses the problem of fault-tolerant integration of abstract sensor estimates.

B. Fusion Methodologies Based on Statistical Decision Theory

The theory of sensor fusion based on statistical estimation and hypothesis testing has been the subject of research in the last two decades [5]. The situation of sensor fusion is substantially more complex in the case of a DSN. More specifically, the problem of constructing decentralized hypothesis testing rules for sensor fusion in the framework of distributed optimal sensor integration theory is the focus of this section. The next six papers deal with fusion strategies in a distributed sensor environment.

The first paper, "Coherent Signal-Subspace Processing in a Sector," by A. Bassias and M. Kaveh discusses three versions of an algorithm that combines the advantages of using prefiltering and subspace alignment of the coherent signal subspace method in the frequency domain for the detection and estimation of multiple groups of wideband signals. The conditional equivalence of these three versions is also presented. The authors also show that prefiltering reduces the computational load. The second paper, "Asymptotic Error Probability Expressions for Multihypothesis Testing Using Multisensor Data," by D. Kazakos discusses the existing upper bounds to the error probabilities and presents the multidimensional version of Chernoff's bound and its relationship to large deviation theory. The author develops new bounds for the error probability in hypothesis testing using the powerful tools of large deviation theory. The necessary and sufficient conditions for the asymptotic convergence of the error rates to zero are determined. Finally, a generalization of the results for multisensor data is presented.

The third paper, "Direction Finding: The Signal Subspace Approach," by J. A. Cadzow uses the wavefront induced sensor signals to estimate the directions of wavefront travel as well as other wavefront related characteristics. The author develops an effective high resolution algorithm for achieving these estimates that is applicable to those cases in which wavefront sources may be coherent and closely spaced. The multiple source location snapshot domain and correlation domain algorithms developed have the attribute of providing high resolution source location estimates independent of the coherency of the incident sources. The fourth paper, "Multitarget Motion Analysis in a Distributed Sensor Network," by P. Ting and R. Iltis considers the data association problem in multiple target bearings-only motion analysis. The authors formulate the problem using the maximum likelihood principle. A stochastic relaxation method based on simulated annealing is proposed to solve the data associations for given trajectory estimates. The Cramer–Rao lower bound of the initial state estimate in the presence of data association uncertainties is derived and compared with the average root-mean-square errors of initial position and velocity estimates.

The fifth paper, "Decision Fusion Strategies in Multisensor Environments," by B. V. Dasarathy discusses efficient decision fusion strategies for deriving optimal decisions in multisensor target recognition and tracking environments. The author presents a method of embedding the fusion paradigm within a recursive system structure to achieve significant enhancement in the reliability of the fused decisions. The final paper in this section, "Linear Imaging with Sensor Arrays on Convex Polygonal Boundaries," by R. J. Kozick and S. A. Kassam establishes that it is possible, in principle, to synthesize the effect of distributing sensors in the interior of a region by using the boundary of a convex region as the aperture. The authors also present signal processing techniques for some standard boundary apertures. The result could be of interest to designers of large distributed sensor arrays. The trade-off involved in using a boundary aperture is the reduction in physical resources at the cost of increased signal processing.

C. Artificial Intelligence and Neural Network Based Fusion

The paradigmatic strength of artificial intelligence and neural networks for potential applications, which require solving intractable computational problems or adaptive modeling arises from their spontaneous emergent ability to achieve functional synthesis, and thereby learn nonlinear mappings, and abstract spatial, functional or temporal invariances of these mappings. Thus, relationships between multiple continuous-valued, statistically-related inputs and outputs can be established, based on a presentation of a large number of representative examples. Once the underlying invariances have been learned and encoded in the topology and strengths of the synaptic interconnections, the neural network can generalize to solve arbitrary problem instances. Since the topological mappings for problem-solving are acquired from real-world examples, network functionality is not limited by assumptions regarding parametric or environmental uncertainty, that invariably limit model-based computational strategies [6]–[9].

The papers in this section discuss the above strategies in a DSN environment. The first paper, "Partial Global Planning: A Coordinated Framework for Distributed Hypothesis Formation," by E. H. Durfee and V. R. Lesser suggests "partial global planning" as a powerful tool for providing a unifying framework for coordinating the actions of cooperating multiple AI systems in a DSN. The results of implementation and evaluation of this technique in a simulated vehicle monitoring application are also presented. The second paper, "Distributed Network-Based Knowledge-Based Systems," by P. Morizet-Mahoudeaux addresses several issues that concern problems in the area of efficient sensor data management. The author proposes an extension of the method used in the design of the system SUPER. The system proposed provides a solution to the problem even when a sensor is out of order whenever qualitative information about the problem is available.

The third paper, "Direction of Arrival Estimation Using Artificial Neural Networks," by S. Jha and T. Durrani presents a neural optimization procedure that utilizes the fast relaxation properties of the Hopfield network to solve the direction of arrival problem. The minimum mean square error cost function of the problem is mapped onto the Liapunov energy function of the Hopfield network that is then used to minimize the cost function. A new method is presented for increasing the probability of convergence to the global minimum based on iterated descent.

The remaining five concise papers consider various computational structures for a DSN environment. The first paper, "Bus Oriented Load Sharing for a Network of Intelligent Sensors," by S. Bataineh and T. Robertazzi considers the load sharing problem involving the allocation of data amongst intelligent sensors interconnected through a bus type communication medium. Three different architectures are considered and for each type, it is shown that the optimal processing time is achieved when all processors terminate synchronously. The authors also examine the interaction between communication and computation.

The second paper, "Performance Evaluation of Distributed Bayesian Detection Structures," by W. A. Hashlamoun and P. K. Varshney deals with the design and performance evaluation of four decentralized Bayesian detection structures. A modified form of the Kolmogorov variational distance is used in the optimization. The design of the optimum system reduces to the optimization of a single function in all the structures discussed. The third paper, "OS Characterization for CFAR Detection with Multiple Sensors," by K. D. Donohue and N. M. Bilgutay presents a new method for modeling clutter statistics in a distributed sensor system. The Order Statistic characterization allows for parallel computations and has the additional advantage of the extra degrees of freedom available for characterization of the statistical behavior of the clutter signal fluctuations.

The fourth paper, "Robot Learning from Distributed Sensory Sources," by F. G. Pin, P. F. R. Belmans, S. I. Hruska, C. W. Steidley and L. E. Parker describes recent work in the area of incremental robot learning. Since learning is an incremental process, much of the basic task and environmental knowledge can be acquired by a robot using simple inferential rules. Three methodologies are presented for the automated acquisition of environmental and task knowledge in a human–robot synergistic system. The final paper, "Multisensor Data Fusion and Decision Support for Airborne Target Identification," by S. Raju and V. V. S. Sarma presents a knowledge-based approach for target identification with implementation details. The authors illustrate this approach with an example in an air–land battle field situation.

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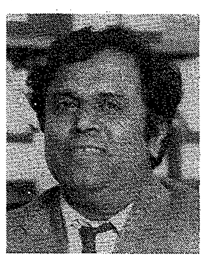

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