The Challenge of Scalable and Distributed Fusion of Disparate Sources of Information

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ABSTRACT

A key enabler for Network Centric Warfare (NCW) is a sensor network that can collect and fuse vast amounts of disparate and complementary information from sensors that are geographically dispersed throughout the battlespace. This information will lead to better situation awareness so that commanders will be able to act faster and more effectively. However, these benefits are possible only if the sensor data can be fused and synthesized for distribution to the right user in the right form at the right time within the constraints of available bandwidth.

In this paper we consider the problem of developing Level 1 data fusion algorithms for disparate fusion in NCW. These algorithms must be capable of operating in a fully distributed (or decentralized) manner; must be able to scale to extremely large numbers of entities; and must be able to combine many disparate types of data.

To meet these needs we propose a framework that consists of three main components: an attribute-based state representation that treats an entity state as a collection of attributes, new methods or interpretations of uncertainty, and robust algorithms for distributed data fusion. We illustrate the discussion in the context of maritime domain awareness, mobile adhoc networks, and multispectral image fusion.

Keywords: Distributed data fusion, disparate data fusion, generalized Covariance Intersection, correlated data, MANET, maritime domain awareness.

1. INTRODUCTION

For the US military to be dominant across the full spectrum of military operations, the Department of Defense's Joint Vision 2020 (JV2020)[1] envisions the

> ... development of a concept labeled the global information grid ... The grid will be the globally interconnected, end–to–end set of information capabilities, associated processes, and people to manage and provide information on demand to warfighters, policy makers, and support personnel. It will enhance combat power and contribute to the success of noncombat military operations as well.

Programs such as FORCEnet and Future Combat Systems (FCS) propose to implement the global information grid through the use of mobile adhoc systems to form sensor networks. These networks will have the capability to collect vast amounts of disparate and complementary information from sensors that are geographically dispersed throughout the battlespace and to fuse this information into a common operational picture (COP). FORCEnet's Expeditionary Sensor Grid (ESG), for example, is shown in Figure 1. The purpose of the ESG is to combine fully netted sensors over robust links to provide (in theory) flawless combat ID and blue force tracking. In turn, this information will lead to better situation awareness so that commanders will be able to act faster and more effectively. Given these benefits, inter-platform information propagation and fusion forms the crux of the Network Centric Warfare (NCW) vision for the US military.

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However, a sensor network provides these benefits only if a number of significant challenges can be overcome. First, the sheer volume of data precludes a centralized, stove-piped architecture and so the network must be able to fuse data in a *distributed* manner. Furthermore, it will be infeasible to simply distribute raw sensor data. Rather, the data must be fused together into some kind of state estimate (or actionable knowledge) that can be distributed. Second, the wide variety of types and kinds of data mean that the state representation cannot be expressed in terms of a simple representation (such as a mean and a covariance). Rather, information needs to be expressed using data schemas that have been derived from ontological analysis. These schemas will encode attribute values, pedigrees, and the relationships that can exist between attribute values. Third, the underlying data fusion algorithms must be able to function in a mathematically consistent way given the constraints of the environment. As an example, the adhoc nature of the network means that the connection topology is in continual flux and is not completely known at any given time. As a result, fusion algorithms that rely on special connection topologies (such as trees or hierarchies) cannot be applied. Finally, almost every Navy information exploitation system — whether doctrinal or automated — is tailored to an assumed set of information sources. If a new source of information becomes available, these systems must be augmented to exploit this information. Therefore, the Navy needs a general and flexible framework for information to be distributed at suitable levels of abstraction so that source-specific information exploitation can be avoided.

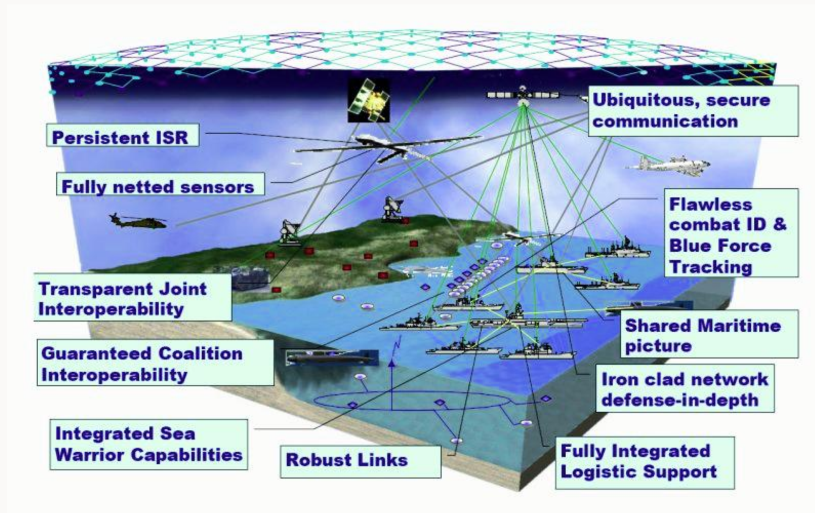

Figure 1. The FORCEnet Expeditionary Sensor Grid. The Grid will provide persistent battlespace sensing through manned, unmanned and unattended sensors. Information sources include intelligence on the disposition and movement of enemy forces, meteorological, oceanographic and terrain data from satellite imagery, tactical radar, autonomous unmanned vehicles, and data buoys.

In this paper we consider the problem of developing Level 1 data fusion algorithms for NCW. We argue that many of the solutions to these problems can be extended from the solutions to more traditional distributed tracking and target identification systems. We describe a proposed solution that consists of three main components: an attribute-based state representation and system models which treats an entity's state as a collection of attributes, new methods or interpretations of uncertainty, and robust algorithms for distributed data fusion.

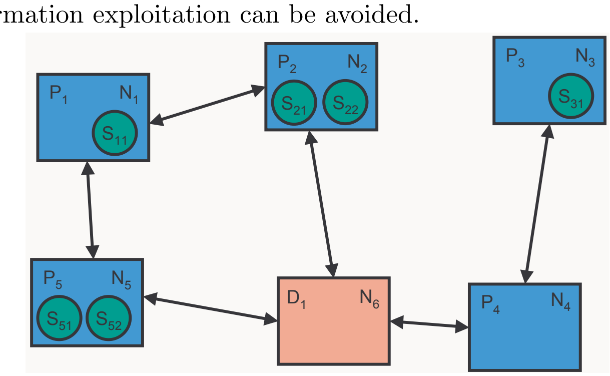

Figure 2. The distributed data fusion network architecture. The network consists of data fusion nodes ($N_\cdot$). Each node can contain zero or more sensors ($S_\cdot$) or databases of aprior information ($D_\cdot$). Zero or more nodes can be associated with platforms ($P_\cdot$).

The structure of this paper is as follows. Section 2 describes the problem in greater detail and justifies the three main issues we have identified. Section 3 describes our approach to state representation. Section 4 groups together the discussion of representations of uncertainty and methods for robust fusion. We illustrate the application of this framework in several complementary problem domains in Section 5. Conclusions are drawn in Section 6.

2. PROBLEM STATEMENT

The sensor grid of Figure 1 can be abstracted to the network diagram shown in Figure 2. The network is composed of a set of *fusion nodes* and communication links between those nodes. Each fusion node maintains its own estimate of the Common Operational/Tactical Picture COTP*. The COTP consists of a set of entities. Each entity is a container of attributes that can include kinematic attributes (position, velocity), identification attributes (entity type, entity class), and sensor signature attributes (such as the affiliation of a target). It should also be noted that there is no fixed correspondence between nodes and platforms. For example, a UAV might be able to use a set of sensing packages. Each package could contain its own standalone fusion node.

The operation of a node is shown in Figure 3: once the state of the node has been initialized, the node predicts the estimate forwards to the time of the next event. Event types include a sensor observation, a report from another node or even a timeout (in which case the observation is null). The information is then fused into the estimate. The scheme for fusion depends upon the measurement process. If the correlation structure of the estimate is known (for example it is guaranteed to be independent), then optimal algorithms can be used to fuse the data. If the correlation structure is known imperfectly (for example because nodes exchange estimates), suboptimal fusion algorithms should be used.

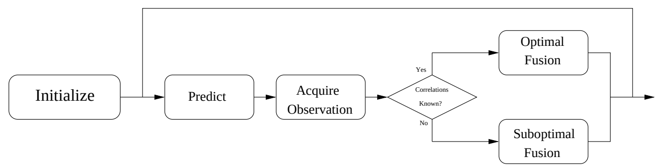

Figure 3. The generalized fusion architecture. This flow occurs on each node in the data fusion network.

The capabilities of nodes can vary in at least four different ways. The first is in the local sensing capability. There are many sources of information from hard sensor reports (such as SIGINT, MASINT, IMINT, IRINT, ACINT, HUINT, and OSINT). More generally, some nodes might perform the role of aggregating and forwarding information and thus possess no sensors. Other nodes might draw data from databases and other offline sources of information. Second, nodes can differ in terms of the signal processing they carry out. A small unattended ground sensor, for example, might perform simple low pass filtering and use crude localization algorithms to localize a target within a fixed detection region. At its most complicated, a node might perform target class recognition using a variety of pattern recognition algorithms, constraining the results using a set of geospatial and other databases. Third, the bandwidth available to each node is different. When the amount of information available exceeds the amount of bandwidth available, it is necessary to be able to summarize the information in a form that satisfies the bandwidth constraint. Finally, the state information maintained within each node for the *same* target can be different. There can be several reasons for this including security (some attributes might be considered privileged and thus distributed to just a subset of nodes[2]), efficiency (some attributes might be entirely irrelevant for another node and there is little point in distributing them), and latency (if an estimate acquires a new attribute, it takes a finite amount of time for the attribute to propagate through the whole network).

The assumption of local communication and the ability to switch between data fusion rules means that such a network is naturally scalable, distributed, and robust[3]. The scalability arises because nodes only need to know about their communicating neighbors; they do not need to know the entire network topology. Robustness arises because there is no single point of failure. If a node or communication link fails, information can flow via alternative routes. However, this configuration introduces a number of difficulties. The first is that efforts must be made to ensure that data is not double counted. Double counting occurs when the same information is fused multiple times into the same estimate and is treated, each time, as containing completely new information. In principle this can be resolved by maintaining a centralized agent that monitors the entire state of the network and all of the nodes at all time. However, the need for such an agent undermines almost all of the advantages of a distributed fusion network. The second difficulty arises because different networks maintain different state

*Note that each node does not necessarily maintain an estimate of the *entire* COTP. Each node performs a specific computing task using information from nodes with with it is linked, but there is no "central" node that controls the network and no node knows the overall global topology. Rather, each node maintains an estate of a subset of the COTP appropriate for the capabilities of that node and the role it serves.

estimates (because of bandwidth issues or security concerns). The effect of using different representations at each node is not, in principle, a difficult problem for a fusion network. The errors in the estimates committed by each node are different but, providing the correlations are maintained between these errors, they can be accounted for[4]. However, this again requires a centralized agent. The third difficulty is that there is the possibility that spurious data, either deliberately or accidentally, can be introduced into the network. Although outliers can occur in any data fusion system, the scale of the network means that such outliers might not be identified at the time they occur and could propagate a significant distance through the network before inconsistencies can be identified.

Given these properties of the network, we believe the following research issues must be addressed:

1. **A general representation of the state.** Because the COTP is being constructed from many different sources, the fusion algorithms must be able to cope with all the different types of information it can be presented with. As an example, an unattended ground sensor might detect the movement of an object in the form of a vibration amplitude measurement, whereas a human observer might provide a descriptive linguistic report: "I saw a white van drive down the street." To capture and express this information, the state representation must be able to describe more than numerical quantities.

2. **New representations of uncertainty.** Although many classes of observations can be represented in terms of a measured state (e.g., a mean state vector) along with some associated measure of uncertainty (e.g., an error covariance matrix), other classes of information are inherently multimodal in the sense that they express multiple *possible* states for a target rather than a single state. In theory this uncertainty can be completely expressed using probability and manipulated using Bayes' Rule. However, any model of the real world is replete with modelling errors. As a result, estimators do *not* propagate the actual probability distribution but some approximation of it. New representations of uncertainty must be developed that are robust to these errors.

3. **Robust data fusion algorithms.** Data fusion algorithms must be developed that can use uncertain states (using the state and uncertainty representations). These algorithms must be robust to double counting and outliers or spurious data, and must be able to fuse estimates of the same target using different state representations.

3. A GENERALIZED STATE REPRESENTATION

The generalized state representation must perform two functions. First, it must be general enough to accommodate a wide variety of information types without abstracting away critical attributes measured by particular types of sensors. Second, it must provide the mathematical equations to be able to manipulate that estimate. Our solution consists of two parts: a generalization of the notion of a "state vector," and a generalization of the notion of process and observation models[5].

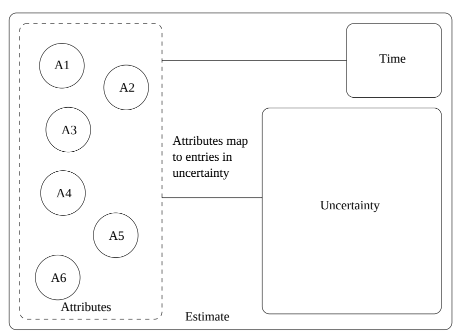

Figure 4. The generalized estimate representation. The estimate consists of a set of **Attribute**s, the **Uncertainty** and the **Time**. The set of **Attribute**s encode the metadata to describe *what* is stored within a given estimate and the **Uncertainty** actually stores this information. All estimates are assumed to be known at a given **Time**.

3.1. Attribute-Container Based State Representation

Many current algorithms for Level 1 Data Fusion are based on the assumption that the structure of the state estimate is relatively limited and static in structure. The simplest and most widely used representation is to assume that the state of a target can be described by a real-valued state space vector of a known, fixed structure. However, as explained above general level

1 data fusion violates both assumptions: the attributes can be non-numerical and the structure of the state estimate, even for the same target, can differ between different nodes.

To address this problem consider the state estimate as a container of attributes whose values are stored in a common uncertainty structure. The structure of this estimate is shown in Figure 4: a container of **Attribute**s, **Uncertainty**, and **Time**.

The most fundamental element is the set of **Attribute**s. Each attribute stores a specific value about an entity or object. The values and meanings of the attributes would be drawn from an ontology. Dorion's Command and Control Information Exchange Data Model (C2IEDM)[6], for example, defines the OBJECT-ITEM at the center of the ontology. Attributes associated with it are the OBJECT-ITEM-LOCATION (where is the OBJECT-ITEM?), the OBJECT-ITEM-STATUS (is it hostile?), and the OBJECT-ITEM-AFFILIATION (what is its geopolitical affiliation?). Not only do attributes have qualitatively different meanings, but they can be quantities of fundamentally different types. For example, OBJECT-ITEM-LOCATION can be expressed as continuous values whereas geopolitical affiliation takes one of a set of a finite number of values. By explicitly encoding the attribute information contained within the estimate, any node can understand what attribute information is available in the estimate that is supplied to it.

The second most significant element is the **Uncertainty**[†]. Almost all real systems and sensing devices contain uncertainty from one source or another and therefore the uncertainty is important as a part of the state estimate. The attributes, however, maintain arrays of indices which show which values in the uncertainties map to the attributes.

The final element, **Time**, specifies the time at which the estimate was calculated and thus the time at which it is valid. In a general distributed data fusion network there is a significant issue with clock synchronization[7] and so the time value should, itself, maintain uncertainty. For this initial design we neglect this uncertainty but note that the data fusion algorithms described later have been demonstrated to be robust to measurements with unknown but bounded time delays[8].

3.2. Composable Models

To execute the filtering loop, the correct models must be used. However, the structure of these models depends on the structure of the state estimate which, itself, can vary through time and across nodes. Rather than construct an exhaustive list for all possible structures of the state estimate, we utilize *composable models*. The principle is illustrated in Figure 5 for a process model. The process model takes the state estimate at a time step k and generates a new state estimate, with the same structure, at time step $k+1$. The model is composed of a set of **ProcessModelStrategy** objects. Each **ProcessModelStrategy** takes an input of a set of attributes and yields an output set of attributes. The input and output attribute sets do not have to be the same. For example, the **ProcessModelStrategy** might take position and velocity attribute information and predict a new position based on the assumption that the velocity is constant. Furthermore, default mappings can be provided if none are defined.

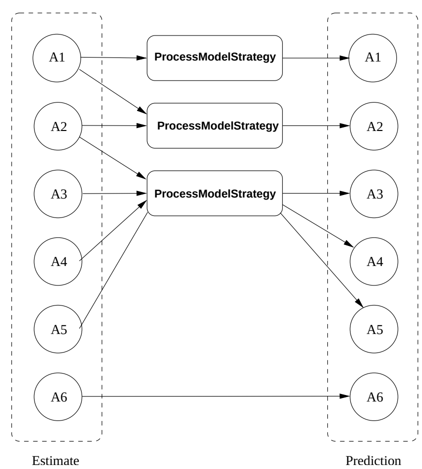

Figure 5. The composable process model is a set of **ProcessModelStrategy** objects. Each object acts on an input set of attributes and yields an output set.

This approach has several advantages:

[†]The uncertainty could be a probability distribution, an imprecise probability distribution or some other representation of uncertainty. See the discussion in Section 4.

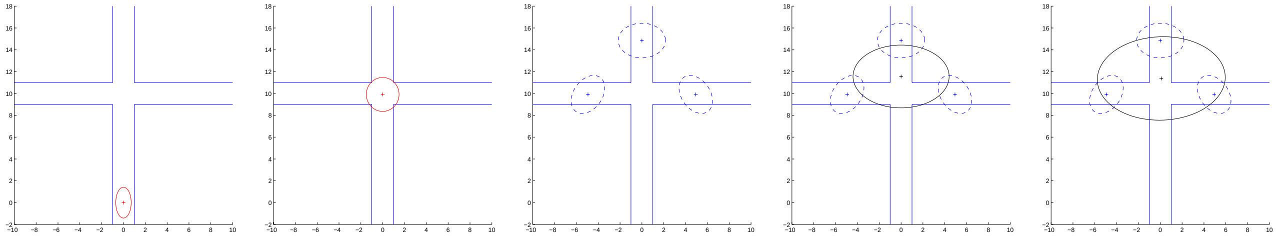

Figure 6. A multiple hypothesis tracking example which shows the mean and 1σ covariance ellipse of the estimated position of a vehicle in an urban environment. When the vehicle reaches the junction three hypotheses can be spawned. Calculating the mean and covariance of the mixture leads to an inconsistent estimate at the junction. Using Covariance Union (CU), a larger covariance estimate is generated. However, these representations represent the multimodal nature of the distribution extremely poorly.

1. The model is composed of smaller units and thus the number of components is greatly reduced.
2. **ProcessModelStrategy** designers need only be concerned about the attributes within their sphere of regard.
3. Different **ProcessModelStrategy** objects can be implemented, using the same state space information, to support models with different levels of fidelity. The choice of the right model could depend on information about the state of the estimate (e.g., the values of certain state estimates) together with contextual information about the node (e.g., high fidelity models might be run on specialized nodes).

The same approach can be provided composable observation and initialization models.

This section has described a generalization of the state space and mathematical models to support disparate data. However, the state estimates are valuable only if an appropriate representation of uncertainty can be defined and robust data fusion algorithms developed.

4. MULTIMODAL REPRESENTATION AND FUSION OF INFORMATION

In the realm of Level 1 data fusion, information is frequently expressed in mean and covariance form, where the mean vector defines the state of the target or system of interest and the covariance matrix provides an upper bound on the expected squared error associated with the mean. The mean and covariance representation information is by far the most widely used in real engineering systems, and the flexibility of the representation is well established. However, the information requirements in many applications are often tailored specifically to satisfy its constraints.

The limitations of the mean and covariance representation of information can be found in a variety of practical contexts. For example, consider the scenario shown in Figure 6: a vehicle is being tracked along a road in an urban environment. Assuming that it travels at a speed that is average for the road, its future position can be predicted forward a short length of time reasonably accurately; however, if it encounters a junction at which it can carry straight on or turn left or right, there are three distinct possible future positions. The future state can be represented with a single mean and covariance estimate, but doing so requires establishing a mean near the junction with a covariance large enough to account for its given any direction in which the vehicle could turn. This is unsatisfactory: the mean vector does not correspond to either of the possible states of the vehicle and consequently has a very large error covariance. Intuitively it seems clear that a better option would be to maintain information about the *three* possible future states rather than subsuming them into a single mean and covariance estimate.

4.1. Representation of Multimodal States

Historically there have been two distinct approaches for representing multimodal information (e.g., as in the above example). One involves Multiple Hypothesis Tracking (MHT), which maintains multiple mean covariance estimates corresponding to distinct possible states. The other approach is to attempt to maintain a parameterization of the Probability Density Function (PDF) that defines the uncertainty distribution associated with state of the target. In practice, PDF approximation methods typically only represent the significant modes of the distribution in terms of their means and covariances, thus making its representation all but identical to MHT. A key distinction is that the PDF-based approach treats the set of estimates as defining a union of Gaussian probability distributions. Both interpretations have the advantage that they can conveniently approximate a wide class of PDFs. For example, in the multiple turn example a single hypothesis can be directed down each arm of the junction. If a state variable takes on one of a discrete number of values (for example, class identity) this can be modeled as a component whose variance is zero. However, using MHT raises an important issue with the question of consistency.

An estimate is consistent if it is "trustworthy" in some sense of the word. Trustworthiness implies that the estimate correctly characterizes its degree of uncertainty. An estimate which claims to be accurate but does, in fact, contain substantial errors cannot be trusted. When an estimate is represented by a single mean and covariance, a natural definition of consistency is that the mean squared error in the estimate does not exceed the covariance maintained by the estimator. As a result, the estimator never under states the uncertainty associated with its estimate. However, no such clear interpretation exists with multi-modal estimates. In particular, each hypothesis has its own weight associated to indicate its level of correctness. We use the definition that an MHT estimate is consistent if at least one hypothesis, irrespective of its weight, is consistent.

MHT offers the potential to provide a general and flexible means of expressing state information. However, there are two issues that must be addressed. First, the fusion algorithms must be robust to effects such as double counting and spurious information. Second, any MHT scheme introduces an exponential increase in the number of hypotheses, and techniques must be developed to reduce the number of modes so introduced.

4.2. Robust Fusion of MHT Estimates

The data fusion algorithms must be robust to both double counting and outliers. In principle these can be addressed by maintaining information about the joint probability between state estimates. However, as explained above this cannot be carried out for any practical network and so schemes robust to unmodeled dependencies must be used. When the estimate is represented by a single mean and covariance, it is now generally recognized that Covariance Intersection (CI) is the optimal solution for maintaining consistent estimates. However, CI can only exploit the first two moments of a distribution and cannot exploit any other information such as the distribution of multiple hypotheses. As illustrated in Figure 6, the resulting estimate can be an extremely crude representation of the true estimate. Therefore, extensions of CI to exploit higher order information are required. We are currently developing two algorithms: one for the case when the weights on the hypotheses are known, the other when the weights on the hypotheses are not known.

4.2.1. Fusion With Known Weights on the Hypotheses

When the weights on the hypotheses are known, one robust fusion algorithm is based on *Chernoff Information*.[9] Given two prior distributions, the Chernoff Information of the solution raises the two components to a power and normalizes the result,

$$P_\omega(\mathbf{x}) = \frac{P_a^\omega(\mathbf{x})P_b^{1-\omega}(\mathbf{x})}{\int P_a^\omega(\mathbf{x})P_b^{1-\omega}(\mathbf{x})d\mathbf{x}}$$

Using a suboptimal approximation for MHT/PDFs, empirical studies have shown that this algorithm yields consistent estimates[10].

4.2.2. Fusing With Unknown Weights on the Hypotheses

When the weights on the hypotheses are unknown, the probability distribution cannot be constructed and Chernoff Information cannot be used. In this case a technique related to CI, called Covariance Union (CU) can be used[11]. CU is used to combine multiple hypotheses into a single hypothesis that is guaranteed to preserve consistency as long as one of the given hypotheses is consistent. For example, given n modes represented by the mean and covariance pairs $(\mathbf{a}_1, \mathbf{A}_1)\ \ldots\ (\mathbf{a}_n, \mathbf{A}_n)$, CU produces a mean and covariance $(\mathbf{u}, \mathbf{U})$ that is guaranteed to be consistent as long one of the mode estimates $(\mathbf{a}_i, \mathbf{A}_i)$ is consistent. This is achieved by guaranteeing that the estimate $(\mathbf{u}, \mathbf{U})$ is consistent with respect to *each* of the estimates:

$$\begin{aligned}
\mathbf{U} &\geq \mathbf{A}_1 + (\mathbf{u} - \mathbf{a}_1)(\mathbf{u} - \mathbf{a}_1)^T \\
\mathbf{U} &\geq \mathbf{A}_2 + (\mathbf{u} - \mathbf{a}_2)(\mathbf{u} - \mathbf{a}_2)^T \\
&\vdots \\
\mathbf{U} &\geq \mathbf{A}_n + (\mathbf{u} - \mathbf{a}_n)(\mathbf{u} - \mathbf{a}_n)^T
\end{aligned}$$

where some measure of the size of $\mathbf{U}$, e.g., determinant, is minimized.

Thus, CU can be applied to the merge potentially conflicting hypotheses together and is guaranteed to yield a consistent estimate: if one of the hypotheses was consistent, then the unioned estimate is guaranteed to be consistent as well.

4.3. Simplifying Multimodal State Estimates

The use of Chernoff Information or CU to generalize CI for application to PDF/MHT-represented state estimates may address the fusion problem, but it introduces a significant practical issue: computational complexity. In the most general case, the fusion of two estimates, each containing N modes, will result in a combined estimate with $O(N^2)$ modes. This quadratic growth obviously cannot be sustained over a long sequence of fusion operations, so mechanism is needed to bound the complexity of the updated PDF approximation while retaining the integrity of the information.

Distribution simplification arises when the uncertainty distribution is to be approximated by a coarser representation. Such approximations occurs to reduce bandwidth and computational costs. Most MHT algorithms for hypothesis pruning identify a mode with a sufficiently small weight, delete it, and redistribute the weight to the other modes. This approach is often unsatisfactory because some number of modes corresponding to the true state of the target will be erroneously pruned. The number of wrongly pruned hypotheses is often larger than predicted because the probabilities/weights are difficult to determine accurately[‡].

CU can be used to overcome this difficulty by merging hypotheses together[12]. The primary technical issue is determining which hypotheses to combine using CU to maximize fidelity. We are developing a utility-based application of CU to reduce MHT information to a form that satisfies constraints dictated by the recipient or by available bandwidth.

5. EXAMPLE

The framework outlined in the last two sections can be applied towards several DoD-critical application domains.

5.1. Maritime Domain Awareness (MDA)

The capability to recognize, monitor, track, and intercept suspect maritime vessels on a global scale is being seen as a major capability that will enable the US and its allies to thwart global terrorist activities[13]. Presidential directive NPSD-41/HSPD-13 Maritime Security Policy (21 December 2004) states that:

[‡]It is important to note that CU preserves consistency at the expense of precision. By contrast, the pruning of hypotheses in standard MHT applications does not maintain information consistency because valid hypotheses may be pruned.

> It is critical that the United States develop an enhanced capability to identify threats to the Maritime domain as early and as distant from our shores as possible by integrating intelligence, surveillance, observation and navigation systems into a common operational picture....

Several factors contribute to this concern, including an increasing threat to the free flow of international commerce arising from an increase in the incidence of piracy and hijacking, the continued use of commercial vessels for contraband smuggling and trafficking (people and/or weapons), and the potential use of commercial vessels to support terrorist activities.

A key challenge in building an accurate maritime common operational picture (COP) is to integrate and fuse multi-source vessel data, and transform the data into useful information and actionable knowledge. This problem is challenging for two reasons. First, information sources are extremely disparate and can include Automated Identification System (AIS), SIGINT (e.g., radar), and acoustics. These data sources can be highly ambiguous and can contain significant outliers. Second, although current data collection systems are highly centralized, the future is likely to include teams of unmanned aerial vehicles (UAVs), fitted with various sensors, to enable the collection, processing and dissemination of data emitted from maritime vessels in the open ocean. Early exercises, such as the Joint Expeditionary Force Exercise (JEFX), are investigating the viability and endurance of using unmanned and autonomous UAVs, such as the Global Hawk, to support the collection of data. With the evolving FORCENet concept and early operational implementations, it is likely that distributed teams of UAVs will share fused information in a decentralized fashion, which will also make it necessary that the algorithms be robust to potentially redundant information (e.g., the "double counting" problem).

The framework proposed in this paper directly addresses these difficulties. First, the use of attribute-based representations mean that the full complexity and variety of information can be represented and associated with a vessel. Second, the use of robust representations and fusion algorithms means that errors — such as persistent human error — can be compensated for. This example also illustrates the scalability of nodes. Some nodes could be UAVs whereas other nodes could be an entire fusion or command center with access to multiple analysts, sensing resources, and databases.

We are currently involved with several MDA-related programs and foresee being able to leverage and utilize the SIGINT and AIS data being collected under those programs to support the enhancements to the fusion algorithms.

5.2. Mobile Ad-Hoc Networks (MANET)

The UAVs described above are likely to depend on Mobile Ad-Hoc Networks (MANETs) for their communications infrastructure. A MANET is a wireless network in which the nodes that participate in the network are mobile and there is dependency on a fixed network infrastructure. These networks are self-organizing. In other words, in order for a node to communicate with some other node, routes must be dynamically determined from the sender to the receiver and this process take places more frequently than in the traditional Internet due to frequent node mobility. Furthermore, in a MANET, every node participates as a router (in contrast to the Internet, where only select computers are designated as network routers). Since a MANET is wireless, the nodes in such a network are more prone to higher error rates potentially caused by interference such as from the environment, media contention caused by nodes in close proximity attempting to communicate on the same channel, or congestion in which a node may begin to drop packets (which may be inadvertently caused by contention).

As already stated, MANET technologies are expected to provide the communications infrastructure for the front-line warfighters (i.e., those at the "tactical-edge" of the battlespace such as the UAV scenario supporting MDA). These types of networks are attractive to the military. For example, a communications infrastructure need not be present in the operating region due to the ability of MANET to support dynamic reorganization in response to the changing network topology. These MANET-based tactical edge networks will also enable reachback into networks that are more stable and managed under FORCENet.

As previously described in the paper, one of the key challenges is to enable the timely dissemination of fused information in a MANET. Since a MANET is more sensitive to the effects of network congestion, it would be highly desirable to isolate congested areas and route information around such areas, thereby increasing the probability that mission critical information will be delivered in a timely manner. For example, through the decentralized exchange of network state information in a MANET, each node could develop appropriate representations to allow that particular node to recognize other nodes that are experiencing congestion and update the local routing table appropriately. We believe the data fusion technologies described in this paper could be applied directly to MANET network state information, so that the two can work hand in glove to deliver fused information in a timely manner. We expect to utilize the NRL Mobile Network Emulator (MNE)[14] and appropriate network simulations[15] to conduct experiments.

5.3. Multispectral, Disparate Source, Image Fusion

Imagery and video are often the most vital information sources in precision warfare including target identification, target localization, damage assessment, coordinated response, surveillance, and intelligence acquisition. For example, acoustic sensors provide initial evidence for weapons fire or explosions over a large urban region. Fusing the acoustic sensor signature information with large covariance, with optical or infrared imagery enables uncertainty reduction and precision targeting. Warfighters or UAVs with visual sensors can be deployed in a coordinated fashion to compensate for occlusions from buildings, environment clutter, shadows, target motion, etc. Such fusion of disparate information can play an important role in urban environments where the tactic of sniper attacks is to shoot-move-hide that results in extracting short motion trajectories from visual clutter. As an example, pan-sharpening fuses high-resolution panchromatic (Pan) imagery with lower resolution multispectral (MS) imagery to yield high-resolution MS imagery[16–18].

The fusion of imagery and video pose is an extremely challenging problem. There are several reasons including the differing sensor characteristics (quantization, configuration geometry, spectral filters) and the need to resample (to project discrete data into different project systems when the camera pose is known imprecisely). As a result, substantial correlations can occur. By treating not only each data source but each processing step in the fusion chain as a sensor node, effects such as unmodeled correlations can be accounted for.

6. CONCLUSIONS

In this paper we have considered the challenge of developing scalable fusion algorithms for disparate sources of information. We have taken the approach of examining issues associated with traditional fusion problems, and we have argued that the same fundamental limitations still exist. We have proposed a new framework for distributed data fusion. This framework uses a general attribute representation to associate general information with state estimates, and robust algorithms for combining this information. We have discussed how this framework can be used to address three DoD-relevant problems.

Results from the present analysis include the following:

1. *An identification of information sources and applications for which traditional Level 1 mean and covariance representations are inadequate to satisfy Navy needs*: It is clear that different kinds of information must be maintained in different forms for different uses. Although this conclusion is not surprising, its implications are important because they superficially seem to suggest that nodes with very different sensing resources and mission objectives cannot be usefully integrated. In other words, such nodes represent independent stovepipes. The only way to facilitate the integration of such nodes is to develop a meta-representation scheme that subsumes the spectrum of representations that can be supported within different nodes. This meta-representation must provide a means for transforming from one node's representation to another node's representation for data fusion.

2. *A new and general information representation methodology*: Two issues relating to information representation have been identified and considered. The first is representational extensibility. Specifically, different sensors may provide information about different attributes of the state of a given target, and different nodes may maintain additional derived attributes (e.g., estimates of velocity, tactical state, destination, etc.). Moreover, the total set of possible attributes is unknown and increases over time with development of new types of sensors. These issues require a representational formalism in which the set of attributes can be dynamically augmented over time. We have developed such a formalism based on an attribute-container

scheme. The second is the issue of representational fidelity. Specifically, the traditional mean and covariance representation is inadequate to encode information about the multiplicity of possible states a given target may assume. We have described how the mean and covariance representation can be generalized using Multiple Hypothesis Techniques (MHT) and Gaussian Mixture Models (GMMs).

3. *New information fusion techniques for MHT/GMM representations*: Defining a flexible and high fidelity information representation scheme is not particularly difficult if issues of information maintenance and fusion are not considered. In order for a representation scheme to be useful, it must admit rigorous and practical fusion algorithms. We demonstrated that traditional Level 1 fusion methods (e.g., Kalman filter and Covariance Intersection) can be generalized for the fusion of information represented in MHT/GMM forms.

4. *Information Representation Compression*: A significant feature of Level 1 fusion algorithms is that they maintain constant computational complexity, i.e., the complexity of the fused state estimates does not increase with the number of incorporated estimates. In the case of optimal fusion of MHT/GMM estimates, this is not the case. Specifically, the number of modes increases as the product of the numbers of modes associated with the set of incorporated estimates. Thus, the fusion of k estimates with n nodes would typically result in a fused estimate consisting of n^k modes. This is clearly impractical. In order to bound the complexity of the fusion algorithm, we have described an approach for summarizing a multimodal estimate with an estimate consisting of a fixed, smaller number of modes. This utilizes Covariance Union (CU) to coalesce subsets of modes into single modes. The attractive feature of this approach is that it is both efficient and mathematically rigorous.

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