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Improving ORM Utilizing Implicit Collaboration & Context Sensitive Fusion

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Abstract**—We depict the functions and extension of a novel information theory based sensors management (ISBM) system to information based sensor and mission management (IBSMM) such that intelligence collection is effective in an expected value sense while remaining independent of any particular platform, sensor or point solution. We describe the proposed implementation via implicit collaboration through common mission goals. Integral to this concept is utilizing the scope of knowledge at each sensing resource in order to provide context sensitive information extraction from sensor data via context-based information fusion.**

Index Terms**—sensor management, sensors, context-based information fusion.**

I. Introduction

Several approaches to sensor management have been postulated including game theory [1, 2, 3], market-based [4, 5], information theory [6] (our papers on information theory are referenced later), expected utility [7], genetic algorithms [8], fuzzy logic [9], evolving fuzzy neural networks [10] and stochastic control [11], as well as several papers comparing these approaches [12, 13, 14, 15]. As an introduction to the content of this paper, we begin with a description of the manner in which our method of information based sensor management (IBSM) maps into Orchestrated Resource Management (ORM). This will be followed by a more detailed explanation of the various components comprising IBSM which have been developed independently over a number of years to instantiate a comprehensive information based sensor management system. Our current interest in IBSM is in expanding it to information based mission management (IBMM) through a new concept introduced here called implicit collaboration.

IBSM utilizes cognitive collection by determining which situation information to collect based on a predicted situation entropy change as computed utilizing a variation of the Bayes net which we call a Situation Information Expected Value net (SIEV-net). This computational procedure produces a *mission goal valued situation information need* which allows an ordering of intelligence needs based on this first type of information we simply call *situation information*.

Intelligence valuation is done by utilizing *goal lattices* which provide a quantitative method of assigning mission goal values to both situation information requests as well as the actual acquisition of that information through sensor observation requests. Goal lattices provide a method of quantitatively associating mission goal values to intelligence needs including the fact that one information acquisition may contribute to more than one higher level information need. The topmost goals of a goal lattice are soft, difficult to measure mission goals which are used to value situation information needs. The bottommost goal values are refined, mission valued, real, measurable sensor actions which can be taken to satisfy situation information needs.

Decision space search methods are implemented in our method of differentiating among situation information requests as well as differentiating among real-measurable sensor actions. Situation information requests are platform and sensor independent. We define applicable functions as those sensing actions which can be performed by the available sensors. From these applicable functions, an admissible set of sensing alternatives which can satisfy the situation information request is chosen. These admissible functions are weighted by their mission valued goal values which tumble down through the goal lattice and form the bottommost layer.

Plan-optimization processes are implemented in an *information instantiator* which evaluates the set of sensor functions currently available (applicable functions) to 1) determine an admissible set of sensor actions, and 2) evaluate each admissible action in terms of duration, goal value, amount of sensor information, and probability of obtaining that information. The result of function evaluation is that the admissible sensor actions are ordered and the one chosen which maximizes the *expected information value rate* (EIVR). No other sensor action can provide a higher mission-valued amount of information with which to decrease the valued situation uncertainty as represented in the SIEV-net.

The goal of the proposed research is to extend our method of information based sensor management (IBSM) to information based sensor and mission management (IBSMM) such that intelligence collection is effective in an expected value sense while remaining independent of any particular platform, sensor, or point solution. We intend to implement collaboration among platforms and platform sensors through the development of our concept of implicit collaboration (IC) through common mission goals which form part of different intelligence collection platforms' goal lattices. Integral to

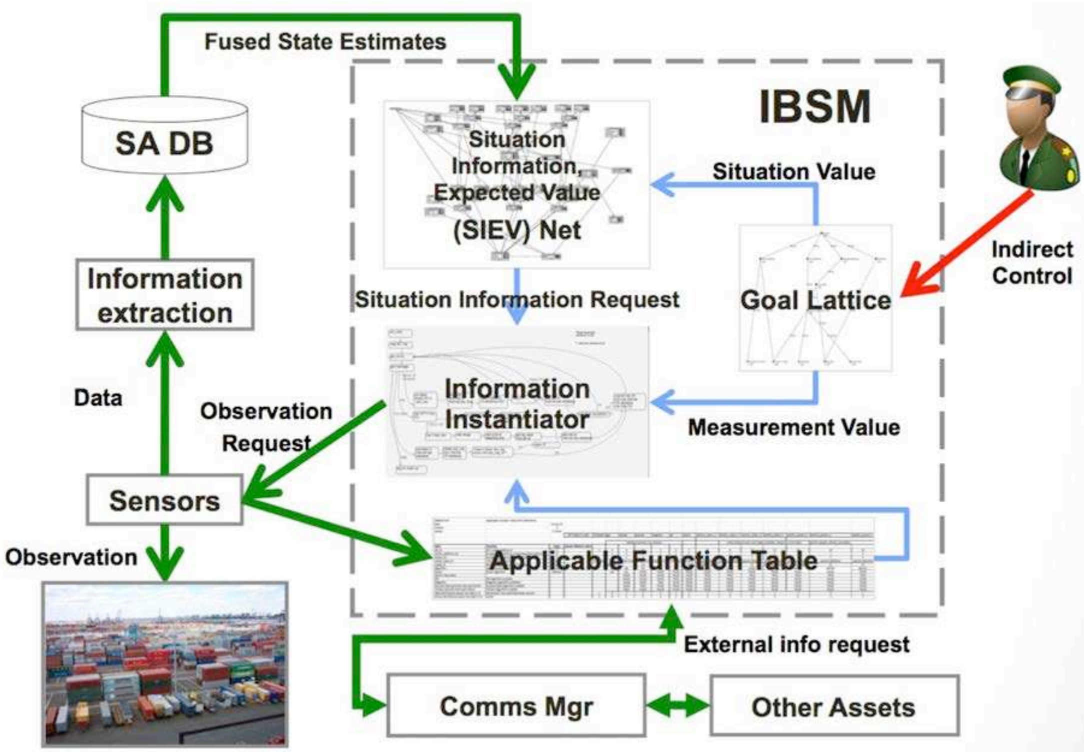

Fig. 1. Block diagram of major components of IBSM shown in central box.

this concept is the utilization of the *scope of knowledge* available at each sensing resource in order to provide *context sensitive information* extraction from sensor data.

II. Information Theoretic Framework

The fundamental concept of our information based sensor management (IBSM) [16, 17] is information theory, namely technical information as measured by a change in uncertainty about relevant aspects of our environment. In our particular case, we measure entropy changes for search, track, and identification although we are working towards utilizing more general forms of measuring information and other types of information. We chose information as our measure because information puts sensor actions in a commensurate measure space which allows direct comparative evaluation of different sensing actions. The second, and operationally significant characteristic of information, is that the amount of information which one can expect to gain by a sensing action is computable even before the sensing action is performed.

The ability to compute the expected amount of information obtainable through a sensor is a necessary, but not a sufficient criterion for requesting sensor actions for most realistic scenarios. It is necessary to adjoin to the computation of information the mission value of that information. To that end, we have developed the concept of a goal lattice and have incorporated its values into our IBSM paradigm [18, 19, 20].

Valued information is necessary, but is still not sufficient to make an effective sensor management system. To be effective and obtain the maximum amount of *information as measured by a reduction in valued uncertainty* in our SIEV-net one must also take into account the time that it takes to obtain that information. The methodology we have developed is that of an *applicable function table* (AFT) which is a formalized way for each sensor or sensing platform to announce its capabilities to the information instantiator (II) [21]. The information instantiator then takes these AFT entries and maps them to situation information requests (SIR) produced by the SIEV-Net [22, 23]. It does this for two reasons, first so that the II can make available to the platform sensor manager (PSM) the information requests that it is capable of responding to, and secondly, so that the II can determine the admissible set of sensor actions from which it needs to select the optimal one to issue to the *sensor scheduler* as an *observation request*.

There is one final parameter which needs to be incorporated in the management of sensors and that is the probability of obtaining the requested sensor information. If this is not exactly computable due to the uncertainty in actual measurements, it is at least computable in an expected value sense for different types of measurements at different ranges for different sensing actions so that it can be used to multiply the valued information rate yielding the expected information value rate [24]. It is this measure that we use to determine which actual observation request to pass from the information instantiator to the detailed sensor scheduler in response to an information request from the SIEV-net.

A. *Expected Information Value Rate*

Unlike Shannon information which guides us in determining the optimal encoding of data which we want to send through a communications channel of known signal to noise ratio (SNR) and bandwidth, we choose to look at information from the point of view of decreasing our uncertainty in a probability associated with a situation. That is, we assume that a sensor can be viewed as a communications channel which is already optimized to transmit data from the process being observed to our current probabilistic estimate of the situation or state of the process. From this point of view, maximizing the information flow into our world model through the communications channel of our sensors reduces to the following:

- Deciding what to measure based on its value to the mission
- Estimating how long it will take to perform that measurement
- Determining the probability of obtaining information from the chosen measurement
- Estimating how much information will be obtained

This reduces to defining the alternative sensor information "channels" in terms of their *expected information value rate* (EIVR) [24] and choosing the measurement to make based on maximizing the flow of what we call the *valued information*.

In a real-time system, there can be no other criteria for minimizing the valued uncertainty in a world model. It is the world model and our best estimate of the state of that world, which is used by humans to make operational decisions about what to do in a particular situation. Changing mission priorities are reflected in human made adjustments to the relative values of the topmost goals in the mission goal lattice. This method of zero sum relative valuation of the topmost goals with no human interaction below that level enables indirect management of the intelligence gathering system while maximizing the valued information flow through the environment sensing channels.

III. Specific Technologies

The specific technologies that we have developed, and in some cases invented, can best be described with reference to a block diagram of an earlier real-time simulation and a walk through the operation of the IBSM system as shown in Fig. 1 [25]. Our primary concern in this simple simulation was the development and demonstration of the theoretical concepts which we have developed, so we implemented the blocks in the IBSM box with high fidelity as well as the real world shown in the lower left and the situation awareness database (SADB) shown in the upper left. The sensors are multiple and heterogeneous, and their behavior is modeled with low fidelity. We also assumed perfect data association and track level fusion rather than measurement level fusion where heterogeneous sensor data are combined.

A. *Goal Lattice*

The methodology begins with the goal lattice in which the human mission commanders apportion the values among the topmost, mission goals which, while easy to state, are soft and difficult to measure. These topmost goal values are available to the situation information expected value network (SIEV-Net) for the computation of the valued situation information of each alternative.

B. *SIEV Net*

The SIEV-Net is a modification of a Bayes net which consists of three different types of nodes: non-managed nodes, managed nodes, and situation information nodes. There are also some computational nodes to convert from managed and non-managed nodes into situation probabilities. The SIEV-Net is more than a Bayes net in that it is dynamic and its structure changes with each newly detected or lost target and with each conversion from detection to track and with each track to type of identified track. Furthermore, the amount of information, as measured by a change in all of the probabilities associated with situation nodes (this differentiates it from an influence diagram), in response to an expected change in a probability in a single managed node, can be computed. So, for each possible situation information request (not sensor action) that could be issued, the amount of information is computed and valued by the topmost mission goals which are apportioned among the situation information nodes. That is, information requests at the situation level are generated independently of the method of obtaining that information which is computed in the II as *sensor information*. The method for obtaining the sensor information is chosen later in the information instantiator (II).

That is, the SIEV-Net is used to apply an ordering to the possible information requests that can be issued by it in order to reduce its valued uncertainty about the state of the real-world, and it does this ordering based on a good, but imperfect model, of what the sensors can be expected to do for it. The SIEV-Net launches an information request to be further refined by the information instantiator.

C. *Information Instantiator*

The situation information request is passed to the information instantiator. The information instantiator determines from the set of functions stored in the applicable function table (AFT) those functions which are admissible, *i.e.,* are able to provide the type of situation information requested within the specified time constraints. In the case of search requests, for each admissible AFT entry it computes the EIVR. In this case, the expected amount of information is based on an expected reduction in the probabilities of the

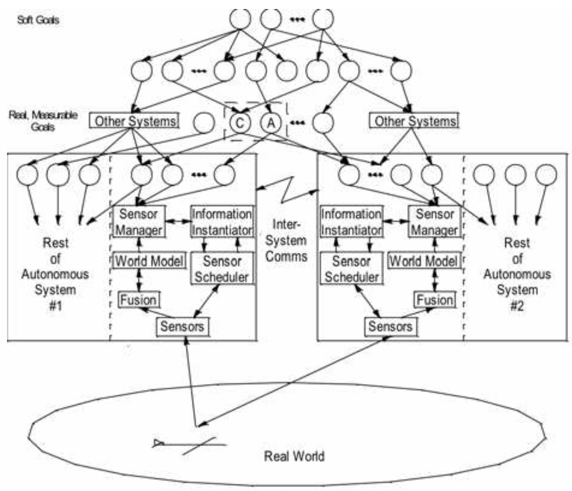

Fig. 2. Goal Lattices of two autonomous systems which include common higher level goals in their individual goal lattices.

ego-centric search probability mass function (SPMF) if a sensor action is performed. While the SPMF display is not shown in Fig. 1 we briefly present its main features here. The SPMF [26] is usually displayed on an egocentric display [27] where azimuth is displayed from 0^o relative to the platforms heading CW to 359^o. Elevation of a sensor beam above the horizon is the radius between the middle circle and outer circle (which is the zenith). Depression of a sensor beam below the horizon is represented by the radius between the central circle and the central dot (which is the nadir). That is, by maintaining a discretized version of the operational environment in a 3-D Cartesian tangential volume, one can compute how much reduction there will be in the probability of an undetected target being in the beam volume for an ego-centric beam passing through that probability volume. The display is pseudo colored to show different probabilities that an undetected target is at a particular beam pointing azimuth/elevation and within that beam. As measurements are made, either in search or track, the 3-D Cartesian volume is updated where the sensor beam passed through it.

In the case of a target kinematic state information request, the present state estimate and target model are utilized to propagate the error covariance matrix, P, using a Kalman filter. A norm is formed of the extrapolated P^- as well as the anticipated P^+ if a measurement were to be taken. If these error covariance matrices are pre- and post- multiplied by a unit normalizing matrix, then the norm can be as simple as the trace of these corrected P's. Another norm which can be used is the determinant of P which, while dimensionally correct, has unusual units. A function of the change in the norm from before to after an anticipated measurement is a measure of the sensor information which is expected to be obtained from that possible sensing action, essentially an entropy change. A similar process can be used for identification request based on a change in the probability of a target being of a particular class. For both of these, the EIVR of the admissible measurements allows them to be ordered.

Once the II evaluates the admissible actions and orders them according to their EIVR, it chooses the one which maximizes the EIVR and passes that as a measurement request to a greedy, priority driven, pre-emptive sensor scheduler. The sensor scheduler performs the detailed allocation of the measurement to a sensor that can perform that function. Once the measurement is taken it is fused with the previous data and the target kinematic and non-kinematic states are updated and the PSM notified that the information that it has requested has been acquired and the process repeats itself.

The concept of differentiating between an information need and its value and the instantiation of that need has recently been updated [28]. It has been shown to be applicable to not only terrestrial assets for which it was originally intended, but also to overhead resources. It is currently common for users who need overhead information to not specify what information they need, but rather which resource to use to obtain that information. This leads to an ineffectual usage of valuable resources.

IV. Indirect Control

It may not be obvious why we chose indirect control of intelligence collection assets rather than direct control, but there are many advantages to this goal directed approach. Indirect control is established by controlling the relative weights of the several goals which drive an intelligence collection platform. That we tell the platform which goals are more important but not how to achieve those goals. The local autonomous platform control system maximizes the EIVR of its sensors whose values are goal weighted and derived from the goal values which are passed to the intelligence collection platform.

Another advantage of indirect control is that we differentiate between information requests and the method of satisfying that request. Notice the use of the word *request* because our view of the collection world is one of *pull* not *push*. The net result of this information pull approach is that it allows for a smaller model of autonomous system/world interaction, and one that can be easily scaled in that it only requires aperiodic unidirectional communications. The only need for a reply from the subservient platform is the fact that it is unable to supply the requested information or the requested information itself within the specified time.

This approach, coupled with a dynamic applicable function table, allows for robust behavior in the event of system or environment degradation. A system under indirect control can continue to operate even if communications are disrupted because it always retains the last set of its topmost goal values from which it makes local value-weighted collection decisions.

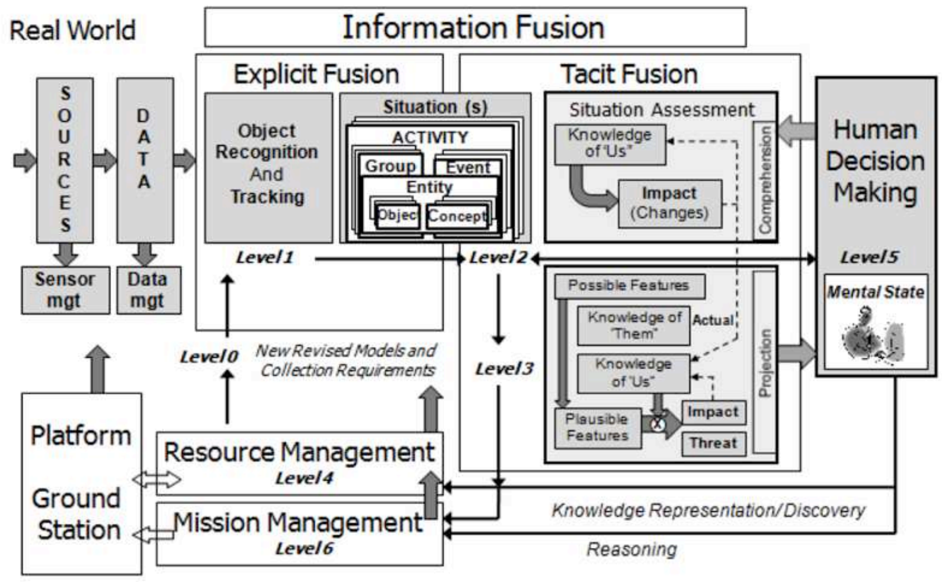

Fig. 3. DFIG 2004 system model highlighting Explicit and Tacit Fusion in 2012

V. Implicit Collaboration

A. Interacting Goal Lattices

While developing IBSM, the interrelatedness of individual goal lattices among different assets on the same side of a conflict soon became evident and we presented the original concept of implicit collaboration through the use of goal lattices in a published paper [29]. Other pressing research opportunities required putting this concept aside although we realized that it would essentially complete the original concept by expanding it to multi-asset, essentially mission management, indirect management of a large number of intelligence collection assets.

In the abstract from [18] we have

A new methodology for quantifying the relative contribution of specific sensor actions to a set of mission goals is presented. The mission goals are treated as a set, and an ordering relationship is applied to it leading to a partially ordered set (POSET) which can be represented as a lattice. At each layer in the lattice, each goal's value is computed as the sum of the (higher) goals in which it is included and its value is apportioned among the (lower) goals which it includes. A system designer is forced to make a zero-sum apportionment of each goal's value among those goals which it includes. The net result of this methodology is a quantifiable measure of the contributing value of each real type of sensor action to the system of goals, leading to more effective allocation of resources. While applied here to sensor scheduling, the method has applications to other decision making processes as well.

From [29], we have

A goal lattice is defined as a set of goals and an ordering relationship defined on that set of goals, where the ordering relation, <, is variously defined as "being necessary for the accomplishment of" or "contributes to the accomplishment of." Since we have a set with a non-symmetric ordering relation defined on it, and a set for which not all orderings are defined, we have a partially ordered set or POSET. If we assume a single topmost goal such as "accomplish mission," and a single bottommost goal of "perform function," we have a lattice. A POSET becomes a lattice when each pair of elements of the set, in this case G, has a least upper bound (LUB) and a greatest lower bound (GLB) as determined by the ordering relation. It is from this property that the name Goal Lattice derives.

B. Implicit Collaboration

Implicit collaboration takes place when two or more sensor platforms contribute to the accomplishment of a single goal that is imposed upon them from a higher level of goal lattice such as the goal lattice of a squadron. The goal structure of a higher level goal lattice is shown in Fig. 2. It is important to note that a squadron may have a real-measurable goal of attacking and neutralizing a target; however this may at the same time be a soft, difficult to measure goal to assign to several assets under the control of the squadron. An example is shown as goals A and C in Fig. 2.

VI. Information Fusion

Information fusion (IF) [30] holds an important role in orchestrated resource management (ORM) and implicit collaboration (IC). As discussed in the previous sections, IF plays a key role in ORM and IC by acting as server of data and information from selected sensors or observed sources by the contextual fusion [31] of data into the desired information as shown in Fig. 1. Data which is fused within the context of the collecting sensor to develop information before passing on to an information requestor facilitates minimum use of communications bandwidth and can reduce transmitter bandwidth and power requirements by not transferring unnecessary data. We refer to this as fusing data within the scope of knowledge or context of the sensing system [32]. The context sensitive information fusion element supports optimum decision making by the system operator/analyst without overloading communications links. It can also support operation in contested environments [33, 34] where communication links and available bandwidth can be limited [35].

It is well known that cyberspace intelligence analysts [36] are overwhelmed with irrelevant information and that only by utilizing big-data analytics-based learning algorithms and data sharing among analysts can the extraneous data be eliminated to reduce intellectual overload and allow rapid decision making. That is, contextual knowledge and analysis of data within the scope of that knowledge plays a key role in effective and useful data fusion.

Contested environments can be produced by jamming, areas of denial, and physical attacks [33, 34, 35]. Under these conditions usual intelligence sources such as SIGINT, COMINT, HUMINT may be unavailable and one needs to look at multi-intelligence MULTI-INT methods via Activity Based Intelligence [31]. Therefore, in contested environment it is essential to perform all source sensing (OSINT) via layered sensing [37] in case context selected sources are unavailable. In this case one can utilize sensors of opportunity (SOOP) [38].

An example scenario: GMTI-tracks-based forensic analysis provides POL data for comparison, but by augmenting (fusing) it with correlated SOOP derived and semantic tracks from OSINT data would significantly aid the intelligence analyst's confidence and reduce workload by eliminating the assessment of extraneous information. SOOP enables passive coherent localization of moving targets, bi-static imaging, and navigation of sensors in addition to SIGINT. Semantic tracks, in part, from semantic metadata, in a given context, can associate (match) information from OSINT and HUMINT data from sensors and cell phones such as entity presence, event, location, etc. and could correlate with other source data. All these functions have to be accessed/activated by the ORM/IC.

VII. ORM & IC

In order show the connection between the ORM and IC we include the well known model known by the fusion community that represents near real world system instantiation of a system, called Data Fusion Information Group (DFIG) model [39, 40, 41]. DFIG replaced the original JDL model of 1987 [42] and is shown in Fig. 3 [43].

Management functions in the DFIG model are divided into sensor control, platform placement, and user selection to meet mission objectives. Level 2, situation assessment (SA), includes tacit functions which are inferred from level 1 explicit representations of object assessment. Since the unobserved aspects of the SA cannot be processed by a computer, user knowledge and reasoning is necessary. Current definitions, [39], include:

Level 0 − Data Assessment: estimation and prediction of signal/object observable states on the basis of pixel/signal level data association (*e.g.* information systems collections).

Level 1 − Object Assessment: estimation and prediction of entity states on the basis of data association, continuous state estimation and discrete state estimation (*e.g.* data/part of information processing).

Level 2 − Situation Assessment: estimation and prediction of relations among entities, to include force structure and force relations, communications, *etc*. (*e.g.* information and knowledge processing).

Level 3 − Impact Assessment: estimation and prediction of effects on situations of planned or estimated actions by the participants; to include interactions between action plans of multiple players (*e.g.* assessing threat actions to planned actions and mission requirements, performance evaluation).

Level 4 − Process Refinement (an element of Resource Management): adaptive data acquisition and processing to support sensing objectives (*e.g.* sensor management and information systems dissemination, command/control).

Level 5 − User Refinement (an element of Knowledge Management): adaptive determination of who queries information and who has access to information (*e.g.* information operations) and adaptive data retrieved and displayed to support cognitive decision making and actions (e.g. human computer interface).

Level 6 − Mission Management (an element of Platform Management): adaptive determination of spatial-temporal control of assets (*e.g.* airspace operations) and route planning and goal determination to support team decision making and actions (*e.g.* theater operations) over social, economic, and political constraints.

It is clear from Fig. 3 and the definitions of the six levels that ORM and IC as shown in Fig. 1 utilize Levels 1-6 and as needed level 0.

Contextual approaches require domain knowledge of the user to support analysis and cueing functions, use of environmental knowledge to guide sensor management, use known distribution of entities for situation assessment (SA), use historical pattern behavior for SA pattern of life (POL), and road information for target tracking on ground or in air from known flight patterns and identification [35]. This topic is the subject of current research.

We will consider two approaches related to the above:

1. Intermediate data/source fusion utilizing implicit collaboration. That is, data fusion when the data/sources are neither distributed nor centralized in which case collaborating platforms obtain data with which to extract information and knowledge that is not available in either source.

2. Intermediate data fusion, scope of knowledge, and implicit collaboration: As above, but with the addition of scoping of knowledge, that is the use of context as discussed above.

The salient new aspect of the proposed research is to consider context as a means for algorithm selection and for the application of it to a selected scenario. Furthermore, we plan to apply context based methods to the two approaches stated above. For the follow-up phase we propose to develop a new problem specific approach and investigate communications service assignment and quality issues [44]. Further, we will use distributed hierarchical fusion without feedback architecture [45] by consider two types of distributed fusion algorithms of practical interest under various assumptions of independence and dependence. Distributed fusion algorithms of practical interest are:

• Bar-Shalom-Campo fusion rule [46], *aka* Track-to-Track fusion (TTF) or Memoryless Fuser which operates asynchronously on-demand. TTF takes into account common process noise because both trackers are tracking the same target, it assumes all common priors are negligible, and it is optimal in the maximum likelihood sense.

• Chong's formula or fusion rule, [45] and [47] *aka* Information Fusion (IF) or Fuser with Memory which requires full rate communications and synchronization. Its advantage over other methods is in its potential implementation simplicity with minimal computational complexity, on-demand operation without the need for synchronization, zero memory store, and operating in bandwidth constrained systems. The IF approach is optimal when there is no process noise, *i.e.*, the target dynamic model is deterministic, and each local update is transmitted to the fusion center exactly at each update time (at full-rate synchronized communications) and accounts for common priors requiring storage.

Neither TTF nor the IF method is optimal in the real world, the performance of the IF is affected by unknown target dynamic maneuvers and time delays such as when full rate communications are not available and when there is a loss of synchronization. While the performance of TTF and IF under non-stressing conditions is known, *i.e.*, deterministic target dynamics and full rate communications without delays, and can be comparable, the use of TTF is preferred over IF because TTF has been shown to have robust performance (*e.g.,* small change of fused state estimate mean squared errors, MSE) in most scenarios even with high maneuvering index (stressing dynamics) targets.

TTF's MSE performance has been shown to be only 7% higher than the optimum centralized fusion even when cross covariance terms (induced at each tracker by tracking the same target) are approximated with a constant, which is the usual assumption in practice [46].

VIII. CONCLUSION

In this paper we depicted salient functions of the proposed implementation of orchestrated research management (ORM) and implicit collaboration (IC) coupled with the use of context based information collection and fusion. Key components/technologies described are the information theoretic framework, including expected information value rate, goal lattice for optimization, SIEV-net for situation probability assessment via SA database, information instantiator coupling goal lattice, SIEV-net, and applicable functions table to control sensors. We plan to develop the system to show that IC is an effective method for indirect control of intelligence collection assets and investigate context sensitive fusion methods as related to IC, and demonstrate the effectiveness of context sensitive information fusion in the context of IC.

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