An Essay to Characterise Information Fusion Systems

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Abstract – Characterisation of an information fusion system (IFS) is a very difficult challenge. There are many levels of information fusion and there are many decision fusion models. One can argue that each problem is very specific and thus developing a generalized framework is utopia. This paper presents a simplified, and sometimes naïve representation of IFS. This representation is based on characterising the inputs and outputs of IFS. An IFS is thus seen as a function that transforms the input into an output given some conditions. These conditions might include controls, background knowledge, and goals queries. We present a set of properties that might be considered to characterise a fusion function. This paper also discusses some challenges of distributed information fusion as a pre-requisite of Net-enabled operations.

Keywords: information fusion, properties, resource management, information quality, uncertainty representation.

1 Introduction

According to the Merriam-Webster dictionary, Fusion could be defined as a merging of diverse, distinct, or separate elements into a unified whole. Information fusion or data fusion is the process of acquisition, filtering, correlation and integration of relevant information from various sources, such as sensors, databases, knowledge bases and humans, into one representational format that is appropriate for deriving decisions regarding the interpretation of the information, system goals (like recognition, tracking or situation assessment), sensor management, or system control [Sander, 1993]. According to the JDL (1999), Information Fusion is the process of combining data to refine state estimates and predications.

The purpose of information fusion is to produce information from different sources in order to support the decision-making process. For example, decision-level identity fusion aims at processing sensor data to obtain identity estimates of a target. Identity fusion can be performed on three levels: raw data level, feature level, or decision level [Li, 2005]. In theory, the fusion of redundant information from different sources can reduce overall uncertainty and thus increase the accuracy of the system. Multiple sensors providing redundant information can also increase the robustness of the system. The fusion of complementary information provided by different sources should results in an *information gain* due to the utilization of multiple sources of information versus a single source. The fusion of information from multiple sources may provide more timely information either because of the actual speed of operation of each sensor, or because of processing parallelism that may possibly be achieved as part of the integration process. Therefore, one can state that the goal of fusion systems is to reduce uncertainty, easy for positional (reduced covariance), more difficult for ID (depends on frame of discernment in DS for example).

The purpose of a fusion system should be tailored towards supporting a decision-maker or a human. Therefore, an information fusion system (IFS) is goal driven. It is constrained by physical and technical constraints. These constraints might include the available sources of information, their quality, environment conditions, processing speed, available bandwidth, uncertainties, etc. The goal might be to declare an identity or to assess a given metric (e.g., speed, altitude). Sometimes, the goal could include assessing the intent. Theoretically, a fusion system is not only required to produce information, but also to identify relationships between information objects and assess the "credibility" of any fused information in context of the decision-maker goal. Therefore, we think that characterising a fusion system should include at least the information sources (inputs), the fused proposition (outputs) and the goals or decision-level queries. This characterisation should also include the background knowledge and the controls that might be applied.

This paper discusses a formal proposition to characterise a fusion system. Section 2 discusses a simplified representation of a fusion system. It is our intention to simplify the fusion problem as a starting point. In our opinion, such a simplification allows to better understand the fundamentals of information fusion. Section 3 proposes a characterisation of the inputs. Topics like uncertainty modelling, quality assessment of sensor data, structured and unstructured information processing are discussed. This section provides a very good overview of the complexity of information modelling and pre-processing prior to information fusion. Section 4 presents a characterisation of the output of an IFS. The outputs are discussed from the decision support perspective. Topics like goal and queries as well as the quality of the output

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information are discussed. Based on this (input, output) model, we propose to discuss the characterisation of the IFS in section 5. Some desired properties or qualities of the information fusion are therefore discussed. Section 6 discusses the net-enabled and distributed information fusion implications. We finally conclude this paper, in section 7, by recalling some of the open problems and summarise the ideas and open questions discussed through out this paper.

2 Formal Representation of an IFS

Let's assume that a fusion system can be represented by Figure 1. This representation intentionally excludes sources control loops for instance. The objective is to characterise the fusion engine or box. The fusion engine may receive processed data, information, knowledge, measurements, etc. The background knowledge might be part of the controls and models provided to the fusion box.

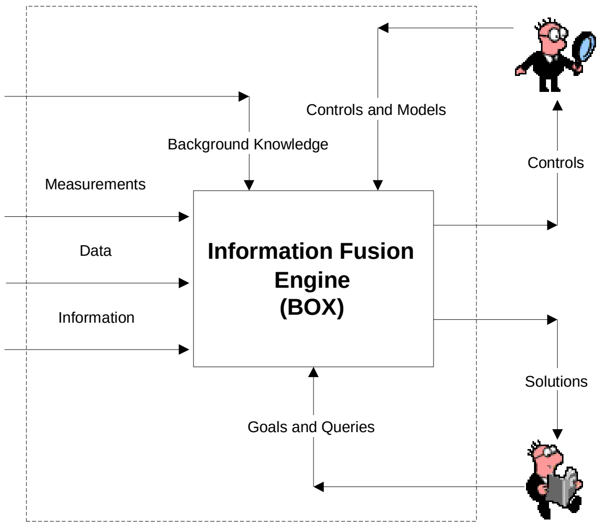

Figure 1.: Representation of a single fusion engine system

Let's consider the following sets **I**, **O**, **F**, **G** and **C** defined as follows:

- **I** is the set of all plausible categories I_j of inputs. Let's consider that each category I_j is defined in such a way as to represent the information, data or measurements available at the entry of the fusion engine.
- **O** is the set of all plausible categories O_k of outputs. Let's consider that each category O_k is defined in such way to represent the solution expected by the design/decision maker from the fusion engine.
- **F** is the set of all fusion functions f that might represent a fusion engine. f: **I** $\rightarrow$ **O** / $f(I_j)\big|_{(C_{jk},G_{jk})} = O_k$ is defined on the set of inputs **I** to the set of outputs **O.**
- **G** is the set of all plausible goals/queries G_{jk} . G_{jk} is a set of goals and queries instantiated to produce the output O_k given that the input is I_j.
- **C** is the set of all plausible controls including the background knowledge $C_{jk.}$ C_{jk} is in itself a set of control parameters, models and background knowledge instantiated to produce the output O_k given that the input is I_j.

Figure 2 is a simplified representation of a fusion function. Let's consider that it is possible to qualify any input I_j and output O_k by a qualification function Q. Q: **X** $\rightarrow$ **Q** / $Q(x) = q_x$ is defined on the set of inputs **I** or **O** to the set of qualities **Q.** For example, if q_x is a confidence level, then **Q** could be a real interval [0, 1].

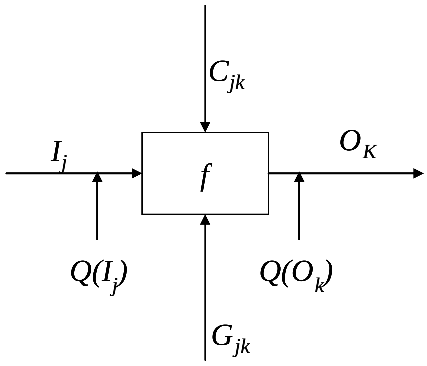

Figure 2.: Simplified representation of a fusion function

The representation in Figure 2 shows the complexity of the fusion problem. The quality and the performance of the fusion function are dependent not only on the inputs, the controls and fixed goals, but also on the quality of these inputs. For instance, for a given goal set, if the inputs and their quality are given, then one might control the fusion function through a good "choice" of the control set. Remember, that the control set might include the formal theories and models to be used by the fusion function. As the reader may observe, this is a very complex problem.

However, for the sake of this discussion, let's simplify the problem. We consider that a fusion problem could be characterised by a couple of (I_j, O_k). Thus, the following matrix represents a typology of information fusion problems:

$$
\begin{array}{c|ccc}
 & & (O_k, G_k) & \\
\hline
 & & \vdots & \\
(I_j, C_j) & \ldots & f(I_j)\big|_{(C_{jk},G_{jk})} = O_k & \ldots \\
 & & \vdots &
\end{array}
$$

3 Characterisation of the Inputs I_j

The information source could be a sensor (e.g., radar, Infrared (IR) sensor, video camera), another IFS, a data base or any combination. When dealing with sensors inputs, the resulting radar cross-section data, infrared or visible spectra, or imagery data are then processed to extract features on the target such as size information, kinematic parameters, movement patterns and shape patterns.

3.1 Quality Assessment of Sensor Data

It has to be realized that different ID fusion schemes may not use the same reasoning framework. Although STANAG 4162 uses the Bayes paradigm, other successful approaches use Dempster-Shafer (DS), and one could also use the recent Dezert-Smarandache (DSm) theory for paradoxical and highly conflicting information, particularly in dynamic situations, or ones that inherently convey fuzzy information. While there are some translations schemes between the frameworks (e.g pignistic possibilities for DS to convey Bayes-type decision making probabilities), it may prove useful to have several reasoning schemes work in parallel, and then weigh the results through some "fusion" scheme such as simple majority voting.

This leads us to the problem of converting sensor data information of various incompatible types to output ID statements (with an associated confidence level) for each of the reasoning schemes mentioned above. This can be the primary role of an Universal Conversion Box (UCB) turning data coming from complementary sensors (active or passive) into such qualified ID statements. This is illustrated in Figure 3 below, where the complexity of the interaction with an Adaptive Fusion Box (AFB) is highlighted.

The UCB will first have to consider intrinsic sensor accuracy for any type of target, subject to degradation by the environment (usually slowly-changing local space-time information gathered from weather reports or other geographical information), and convert it into appropriate ID statements with confidence level, for the appropriate level of reporting of the sensor (category, type,…, all the way to specific platform ID), and for the chosen taxonomy (e.g. MIL-STD 2525B or STANAG 4420). This intrinsic sensor accuracy is however subject to modifications by the performance of the fusion box, when the latter provides indications of local poor performance through MOP, MOE evaluation for any given target. This info can be used to locally discount the confidence on sensor reports in a given space-time region for specifically identified "difficult" targets. Because these "difficult" targets are likely to be of a hostile nature, the time-frame involved is much quicker than for the UCB, since it is driven by fast changing local space-time info (high densities of targets typical of a coordinated attack, hostile target manoeuvres, etc.).

Naturally, the quality of the resulting ID fused information is highly dependent on the detailed attribute information resident in the a priori Platform DataBase (PDB), which correlates measured sensor data attributes (of geometrical or kinematical nature) with platform IDs. Some sensors provide a more direct measure of the identity, such as an ESM, IFF, or classifiers for imagery sensors. At present, the PDB contains approximately 2,200 platforms (700 airborne platforms, and the rest consists of ships and submarines) [Bossé et al., 2006].

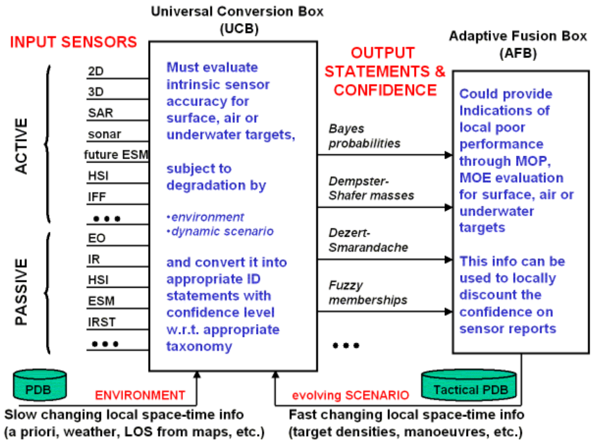

Figure 3.: The Univeral Conversion Box interacting with the Adaptive Fusion Box

3.2 Uncertainty Modeling

Most sensors and information source models provide estimates. Usually, an IFS has to process uncertain and imprecise information. Communicating the uncertainty or the quality of the information should be an important requirement of any IFS. It is important to know not only the quality of the information, but also the type of uncertainty represented. For instance, information uncertainty could be represented by a distribution of probability, a possibility function or a fuzzy membership function. These three different types of uncertainties require different processing means and convey different messages. A variety of approaches have been used, with different assumptions, definitions and interpretations.

The information represented by an Input I_j might be a signal produced by a sensor or a declaration resulting from information processing. For example, a sensor might send its raw data or target identity estimation. Such data or information might be uncertain and imprecise. The uncertainty could then be represented by probability theory, fuzzy set theory, possibility theory, interval algebra, evidence theory, or rough sets theory. In case of multiple sources of information fusion, the input might contain several combination of uncertainty modelling objects. For example, the input could be represented by a probability and fuzzy variables. Therefore, how does one process these two forms of uncertainties? How does one assess the resulting information fused from these two forms of uncertainty?

Dealing with and understanding the effects of uncertainty are important tasks for the information fusion field. Reducing the effects of some forms of uncertainty without catastrophically increasing the effects of other dominant forms should be one target of information fusion. Moreover, understanding the implication of such uncertainties on any decision-level model should be clearly understood. Robust fusion should allow specifying model uncertainty and taking into account all plausible scenarios. Robustness analysis should help to analyze the potential degradation in stability and performance of system brought on by the input uncertainties and plausible scenarios.

4 Characterisation of the Outputs O_k

In case of multi-sensor information fusion, the output might be a combination of features on a target such as its size, kinematics parameters, position, movement pattern, shape pattern, etc. Moreover, more complex constructs could be generated like the intent, relationships between targets and behavioural predictions.

Let's consider the example proposed by Li et al. (2005). Suppose a set of *n* exhaustive and mutually exclusive proposition for the target identity, $a_1, a_2, \ldots, a_n$; for example: a_1 = "*target is friendly fighter aircraft*", a_2 = "*target is hostile fighter aircraft*". It is important not only to identify which proposition, but also to associate a "credibility" or plausibility of such a conclusion. In our opinion, the output of the fusion process should be tailored and guided by the decision making problematic. Therefore, characterizing the output of an IFS should start by identifying all possible decision-making queries that a human might input in order to make a decision in a given situation. For example, a decision might be identify a target, or recognize a specific behaviour. The recognition of the identity or a pattern is not enough. The end-user or decision-maker requires a level of confidence to be attached to such fused information in order to understand the level of risk he might be taking by using a countermeasure or performing a hard kill attack. Understanding implications and possible employment of the fused information requires that the IFS produces qualification of the output with any information produced.

A rigorous analysis of all IFS output should be carried out. Then a unified fusion framework should be developed in order to guide the design of IFS.

5 Desired properties of IFS

In this section, we discuss the desired or fundamental properties of an IFS. We recognize that these properties are neither universal nor exhaustive. But, it is important that the information fusion community develops the foundation for an information fusion theory that will guide development and employment of information fusion models and concepts. These properties are not neutral and are guided by the decision fusion model. The following properties are proposed based on multiple criteria decision analysis work. These properties are indicative of the kind of formal study required to characterise the information fusion function *f* (model).

Property 1: Neutrality (or unbiasedness)
Under the same control conditions and goal query, the output O_k of a fusion function *f* should only depend on the content of the input I_j. In other words, under the same conditions, *f* should not be dependent on the order in which the sensors inputs are processed. This property could be formulated as follows:

$$if \begin{cases} f(I_j)\big|_{(C_{jk},G_{jk})} = O_k \\ and \\ f(I_l)\big|_{(C_{lk},G_{lk})} = O_k \quad \Rightarrow I_j = I_l \\ and \\ (C_{jk},G_{jk}) \equiv (C_{lk},G_{lk}) \end{cases} \tag{1}$$

$$if \begin{cases} f(I_j)\big|_{(C_{jk},G_{jk})} = O_k \\ and \\ f(I_l)\big|_{(C_{lk},G_{lk})} = O_k \quad \Rightarrow (C_{jk},G_{jk}) \equiv (C_{lk},G_{lk}) \\ and \\ I_j = I_l \end{cases} \tag{2}$$

$$if \begin{cases} f(I_j)\big|_{(C_{jk},G_{jk})} = O_k \\ and \\ f(I_j)\big|_{(C_{jl},G_{jl})} = O_l \quad \Rightarrow O_k = O_l \\ and \\ (C_{jk},G_{jk}) \equiv (C_{jl},G_{jl}) \end{cases} \tag{3}$$

Property 2: Consistency (Condorcet or Pareto principle)
One could define multiple versions and variations of this property. In the case of a single sensor reporting, the proposition produced by *f* should be consistent with the sensor report. Let's consider multiple sensors reporting the same proposition on a given target. *f* is said consistent if and only if O_k is consistent with any report of any reporting sensor. A relaxation of this property might be articulated for a coalition of sensors instead of all sensors. For example, another version of consistency could be defined based on the known governing laws (e.g., the laws of physics).

Property 3: Monotonicity
Let's consider that for a given input I_j, the fusion function *f* produces the output O_k with a quality $Q(O_k)$. Then, if an additional source of information is added and that source of information supports the output O_k, the O_k should be reinforced and the quality $Q(O_k)$ increased. For example, if the output is a proposition a_1 with a likelihood $Q(a_1)$, and if an additional sensor is added and that sensor produces a report in favour of a_1, then the fusion function should reinforce the proposition a_1. A relaxed version of this property might be defined.

Property 4: Significance (preserving the data)
The significance is based on measurement theory concepts [Krantz et al., 1971]. Any processing involved by a fusion

function f should respect measurement theory principles. That means that any transformation of the information required by any fusion model in f should respect the significance authorised transformations.

<u>Property 5: Risk of fusion errors (Real and Empirical Risk)</u>
Based on the fusion function f transformation, the real risk R(f) should represent a boundary on the expected maximum error risk for a given situation $f(I_j)\big|_{(C_{jk},G_{jk})} = O_k$. The risk of fusion error is inspired from statistical hypothesis test analysis and machine learning; what is the risk that the fusion function might produce a wrong solution? Given that it is difficult to determine a boundary, it is possible to introduce an empirical risk estimation $R_z(f)$. One way to assess such a risk is to develop benchmarks on given problem sets. For example, consider a set of targets and separate it into two subsets. The first subset will be used to train the fusion function and the second to validate it. Recording the distribution of errors, it will be possible to estimate an empirical risk of fusion error for that given problem. A generalisation of this risk might help in estimating the real risk. Then, the decision-maker will know a priori the risk of a given fusion function f when used in a given context $R_z(f(I_j)\big|_{(C_{jk},G_{jk})} = O_k)$.

The above are theoretical properties. It is possible to develop other properties. This is an ongoing work. We would like to introduce also pragmatic properties. Those properties that are required to help in explaining and validating the results of a fusion function f. For example, we retained the following properties:

- Conviviality of the fusion function: this property is concerned by the simplicity to employ a fusion function f. For example, information overload, controls, complexity of the processing are examples of indicators to assess such a property;
- Transparency of f: this property is concerned by the black box effect. It is important to be able to explain and replicate the result of a fusion box. This might help the end-user understand the limitations of f.

Many other properties might be considered. A rigorous and thorough effort should be employed in order to characterise each fusion function f. We foresee that such a characterisation is context dependent. Therefore, the characterisation process should be performed for each cell of the Input/Output matrix.

6 Example of practical distributed Information Fusion System

Having described properties of one IFS, we now turn to the problem facing decision-makers in a networked environment of a very large number of IFSs, with supporting data coming from a large variety of sources to support the intelligence and operations loops. The problems discussed in this section are typical of any coalition operation.

The military model depicted in Figure 4 below contains two intertwined and equally important loops:

- The first is the familiar operational real-time Observe-Orient-Decide-Act (OODA) loop (on the right) acting on current (usually structured) data, and it must be completed faster than the opponent. ISR assets and situational data help the OODA loop function in the appropriate context; and
- The second is the Intelligence cycle (on the left), with corresponding processes such as collect, index and organize, with subsequent steps of processing, collating, evaluating, analyzing, integrating, synthesizing, interpreting, producing and disseminating intelligence, producing final plans and directions, for further starting another loop, again at a faster pace than the opponent. This loop functions on non-real-time background information or knowledge, typically of an unstructured form, such as document containing doctrines, lessons learned, etc.

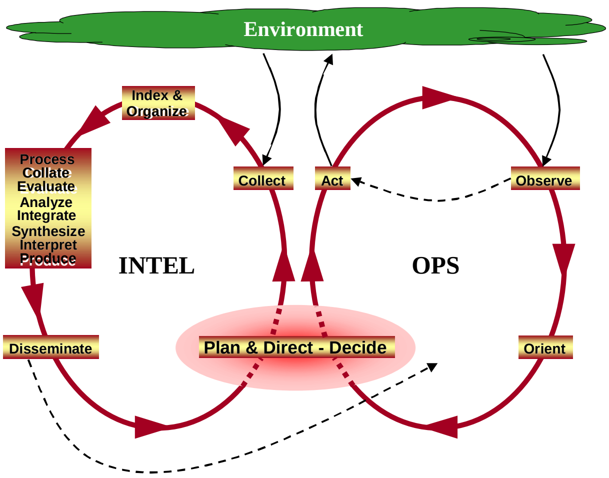

Figure 4.: Linking the OODA loop and the intelligence cycle [Roy et al., 2005]

The information capability is therefore a key component to process the dispersed and scarce information into actionable information that support the Commander's decision making process. Thus, the decision fusion model should guide any fusion system output. O_k should therefore be defined in a context of the C4ISR.

Canada and its allies have identified the vulnerability of the sea-lanes and their ports and harbours to a variety of terrorist threats and illegal activity of many kinds [Maritime, 2005; Coastal, 2005]. The "White Shipping Problem" has become a main interest for the defence research community on information fusion and decision support [Submarine, 2005]. With one of the world's longest coastlines, Canadian concerns in White Shipping are primarily focused on the integrity of their very rich fisheries in the economic zones off the coasts of Canada. Gaining a current operating picture in such situation requires information gathering with multiple sensors (e.g., optical, infrared, SAR) on multiple platforms (UAVs, aircraft, helicopters, ships, satellites) to enable quick wide area coverage. Communication links extend from the current data link systems to satellite links. This is schematically depicted in Figure 5 for maritime patrol aircraft (CP-140), helicopters (MHP), UAV swarms, ships, and ground units.

Distributed information fusion will require developing new innovative architectures and investigation of information imperfections and possible source correlations. Other means used to identify ship "drop outs" or other changes in behaviour depends on the ability to maintain persistent surveillance and consistent tracks utilizing continuous reporting. This is also true of other dynamic reporting systems such as the intercept of radar and communications signals by national or tactical sensors, acoustic signals by national means from a number of allied nations. High-Level Fusion functions such as aggregation of assets, intent prediction, and resource allocation for the White Shipping problem has not been done yet across the allied nations. Aggregation of White Shipping tracks is not yet achievable.

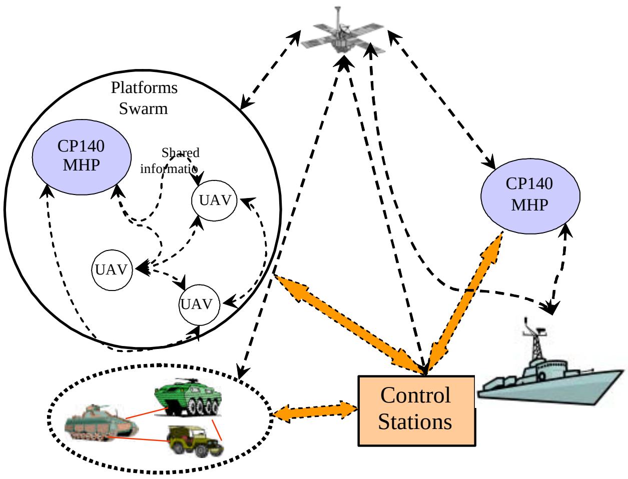

Figure 5.: Fusion nodes with reporting platforms in a distributed environment

Quite frequently, additional unstructured data in several forms including textual information will be available in addition to the surveillance information. The new data needs to be seamlessly fused with the obtained surveillance information to provide an improved surveillance performance. Hence, the problem of fusing structured information with ad hoc unstructured data has to be investigated. The unstructured data will be semantically classified based on their keywords and ordered based on the relevance to the structured data available on hand. The classified unstructured data based on the keywords will then be associated with the structured information fused from several sources. Advanced algorithms will be designed to perform contextual fusion of unstructured data with structured information.

Finally, without the ability for resource allocation or Level 4 fusion capabilities across the allies to task assets, sensors, and platforms to gather appropriate data for white ship tracking, the fusion problem is unable to be solved optimally because of lack of data. The lack of data leads to problems with higher level fusion reasoning algorithms which try to aid operators with the current situation. Dynamic management of surveillance platforms should optimize assets allocation and improve adaptability as new information is gathered. In particular, the platform's areas of operation are dynamically allocated to improve the quality, and accuracy of the fused information. For example, the resource management algorithms should be designed to maximize coverage, maximize probability of success, minimize risk, and minimize response time to unforeseen events. Dynamic programming optimization, evolutionary computation, constraint solving algorithms, stochastic local search techniques and control theory are to be investigated to design near-real-time adaptive platform management solution [Belfares and Guitouni, 2003; Belfares et al., 2006; Bellman, 1957; Boukhtouta et al., 2003; Guitouni et al., 2003; Guitouni and Belfares, 2004]. The coordination conflict arising from communication link failure between two platforms will also be investigated in this light and, based on the investigations, robust dynamic resource management algorithms for specific applications will be developed and tested.

Of course such NEOps operations will require new tactics and doctrines for engagement. Distributed information fusion requires generalising the proposed formal framework.

7 Conclusions

This paper discussed a formal proposition to characterise a fusion system to better understand the fundamentals of information fusion. It proposed a characterisation of the inputs on aspects like uncertainty modelling, quality assessment of sensor data, structured and unstructured information processing and a characterisation of the outputs from the decision support perspective such as goal and queries as well as quality of the output information. Based on this (input, output) model, we discussed the characterisation of the IFS by defining desired properties or qualities of the information fusion. The last section discussed the net-enabled and distributed information fusion implications and the military context of application.

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