Measures of Effectiveness for High-Level Fusion

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Abstract *– Current advances in technology, sensor collection, data storage, and data distribution have afforded more complex, distributed, and operational information fusion systems (IFSs). IFSs notionally consist of low-level (data collection, registration, and association in time and space) and high-level fusion (user coordination, situational awareness, and mission control). Low-level IFSs typically rely on standard metrics for evaluation such as timeliness, accuracy, and confidence. Given the broader use of IFSs, it is also important to look at high-level fusion processes and determine a set of metrics to test IFSs, such as workload, throughput, and cost. Three types of measures (measures of performance MOP, measures of effectiveness MOE, and measures of merit MOM) are summarized. In this paper, we seek to describe MOEs for High-Level Fusion (HLF) based on developments in Quality of Service (QOS) and Quality of Information (QOI) that support the user and the machine, respectively. We define a HLF MOE based on (1) information quality, (2) robustness, and (3) information gain. We demonstrate the HLF MOE based for a maritime domain situation awareness example.*

Keywords: *Fusion, Situational Assessment, Interface Design, Knowledge Representation, User Refinement*

1 Introduction

The objective of this paper is to initiate a discussion on an appropriate set of effectiveness metrics for high-level information fusion (HLF) evaluation. We suggest that *HLF effectiveness* has three parts: information gain, quality, and robustness that we develop in the paper.

The distinction between high-level and low-level fusion has propagated from the 1980's discussions surrounding the needs and the relevant processes for information fusion. The Joint Director of the Lab's (JDL) model and its subsequent revisions formed the high-low level distinction [1, 2].

Figure 1 shows a correspondence between the JDL model and the updated Data Fusion Information Group (DFIG) model in which the user is an active part in the fusion process. From the numbering scheme, HLF includes all levels beyond that necessary to track and identify objects (found in Level 1 Fusion). **Level 1** fusion, including the physical-based parameters, lends itself to quantifiable evaluation techniques. Current directions in measures of effectiveness (MOEs) for information fusion systems (IFSs) [3] need to address approaches beyond estimation (determining parameters from measured data) and fusion rules [4].

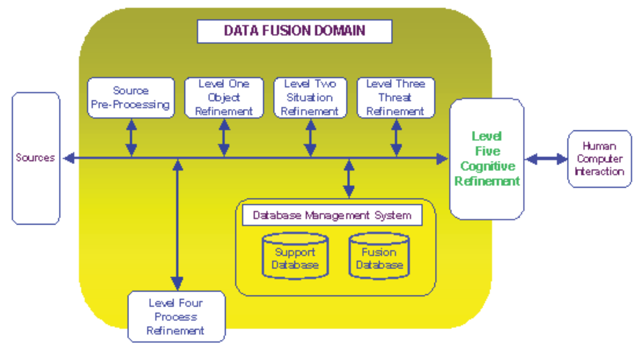

Figure 1. JDL fusion model revision (D. Hall).

Evaluating an information fusion system is not new. There is a large set of literature associated with measures of performance (MOP), MOEs, and measures of force effectiveness (MOFEs) based in estimation. Two excellent summaries include Ch11 from Waltz and Llinas [5] and Ch 20 from Llinas [6]. The compiled information from [5,6] represent a comprehensive assessment of methods in estimation MOP/MOEs and discussion of HLF issues. However, addressing fusion process MOEs [7] as a system infers the need for additional discussion on HLF performance metrics in real systems [8]. Systems perform well if they (1) support mission goals [9], (2) enhance operator work tasks [10], and (3) reduce uncertainty [11, 12].

Effectiveness implies that a system is capable of producing an effect. Many benefits of fusion include providing locations of events, extending coverage, and reducing ambiguity and false alarms [5]. The goal for the IFS is to support the user in their tasks whether providing refined information, reducing time pressures, or determining completeness, accuracy, and quality in task completion. Effectiveness issues include:

- *efficiency*: doing things in the most economical way (good input to output ratio)
- *efficacy*: getting things done, i.e. meeting targets
- *effectiveness*: doing "right" things, i.e. setting right targets to achieve an overall goal (the *effect*)

http://en.wikipedia.org/wiki/Effectiveness

Inherent in the definition of "effectiveness" is a level of performance needed to accomplish a goal. While a large number of ideas and metrics could be postulated; all having their merits and limitations, we focus on three:

- *Information Gain* = valued added from which two pieces of information provide more content than individual pieces of information alone
- *Quality* = Measures of Performance that includes accuracy, reduction in uncertainty, confidence, credibility and reliability
- *Robustness* = consistent over domains of testing and application

Together, these definitions form the basis of "effectiveness" in (1) presenting high quality data, (2) being derived from more than one source, and (3) being consistent and reliable over the situation. These operating conditions from the object, sensor, and environment form a strategy for looking at effectiveness. We postulate a general HLF MOE as:

Effectiveness = InfoGain * Quality * Robustness

A taxonomy of other metrics could be expanded upon, in order to create an evaluation standard for MOEs. However, different environments would necessitate adaptive metrics tailored for the situation [13, 14, 15].

The rest of the paper is as follows. Section 2 overviews the distinctions between low-level and high-level fusion (HLF) with emphasis on background research in HLF. Section 3 describes MOEs as derived from quality of information and quality of service. Section 4 postulates a high-level MOE based on domains of information gain, quality, and robustness. Section 5 provides a maritime example. Section 6 includes discussion and a conclusion.

2 Background

Since the 80's, there has been a distinction between HLF and low-level fusion (LLF). The distinction was made between traditional methods of control, estimation, and integration methods versus reasoning over relationships, entities, and global predictions. Such a distinction is made between physical processes and situational reasoning.

Currently, there is a need for systems to determine the intent observation [16, 17], threat prediction [18], situational awareness [19], situational analysis [20], situational prediction [21], force aggregation [22], cyber analysis [23], sensor placement [24], and political analysis [25]; all of which is a holistic interpretation of fusion systems [26] and events.

2.1 Low-Level Versus High-Level Fusion

The distinction between LLF and HLF is based on the original JDL model and its subsequent revisions [1]. The original JDL model and its developments, shown in Figure 1, highlight the fact that the fusion levels are developed as processes that support a user from translating data from sources into information for user and process refinement [27, 28] and displays [29, 30]. The distinction between LLF and HLF data fusion is based on the objective or subjective components that are available to the fusion system, and the community is developing tools for fusion assessment [31, 32]. While there is no formal definition of HLF, it is referenced to the Information Fusion model and featured in articles [33] and texts [34]. It is suggested that the community determine a terminology that confers the meaning of the information fusion processes.

Low-level data and information fusion typically concerns objective and measureable quantities. Determining a target location and identity is an example of a measureable quantity [35, 36]. State estimation and control can be achieved through LLF concepts. The original JDL definitions of Level 0-1 were estimation of states: objects, locations, and identities [1]. Thus, a summary of LLF is objective estimation (of objects) through observations.

High-level fusion involves the complex, command, and contextual information that is subjectively reasoned and analyzed to determine the Level 2-5 situation, threat, and the operational usability of the information supplied to a user. Recent texts [32, 34] address techniques for HLF.

Various processes can be both *high and low level fusion* and can be constructed in a hierarchical fashion to support information and knowledge management [37] and decision support [38]. Such techniques of data mining, user reasoning, resource control, and situation assessment have attributes of both high- and low-level fusion [39].

2.2 High-Level Fusion as a form of Reasoning

Information fusion is growing as a technique of interest to the systems engineering community. Thus, it is important to arrive at a terminology that conveys the methods proposed. One distinction (out of many) to consider is the *reasoning* applied to the various "levels" [27]. A duality exists between reasoning, much as the duality between estimation and control [1] used to formulate the JDL model. Table 1 lists some reasoning methods.

Table 1: Reasoning Methods

	Inductive	**Deductive**	**Abductive**
	Infer A from B given instantiations of A and B	Derive B as a consequence of A	Infer A as an explanation of B
	Observe instances to generate understanding	Observe consequence to infer cause	Derive explanations from observations and theory
Based on	Evaluate specific observations or situations	Laws and principles	Subjective and conditional logic
Method	Probability, Bayesian, entropy	If-then, Hypothesis Tests	Bayes Nets
Purpose	Specific to general	General to Specific	Incorporate relations

Deductive reasoning arrives at a specific conclusion based on generalizations of physical laws through such means as hypothesis testing. Inductive reasoning (through experience) takes events and makes generalizations. Abductive reasoning (e.g. Bayes Nets) allows for an explanation of unrelated data. The type of reasoning affects system evaluation.

2.3 IFS Evaluation

Information fusion systems (IFS) include the technology, algorithms, and environment of operation (to include the people). Moving from LLF to the abstract reasoning requires integrating the user into the analysis, such as for command and control. For a system to be operational, it needs to verified (LLF question) and validated (HLF question); described briefly as:

Verification: "Am I measuring the IFS correctly?"
Validation: "Am I measuring the correct IFS?"

For instance, in an example of operational maintenance; the normalized timeliness metrics [40] are separated to verify individual machine performance as:

$$\text{Overall Equipment Effectiveness \%} = \text{Available \%} \times \text{Perf. Efficiency \%} \times \text{Quality Rate \%}$$

As per our definition, we bring to light the need for the information gain in establishing the timeliness, accuracy, and confidence associated with an IFS's ability to help the user reason over data, make decisions, and act on the information. Evaluation looks at the quality of information.

2.4 Quality of Service/Information Research

To address the MOEs at high and low-level fusion, we need to look at the quality measures being developed over various domains and reasoning methods. Industry standard definitions, utilized in Section 3, come from QOS [46] and QOI [49], respectively.

In Fusion 2005, Johnson and Chang [41] proposed Quality of information (QOI) for data fusion in net centric "publish and subscribe" architecture to "update clients in a QOI paradigm rather than a quality-of-service (QOS) paradigm". They varied the message length in a QOI system versus fixed time metrics in a QOS system. To facilitate end user's needs in a net-centric environment, a QOI was used because of sensor-web enabled ontology development. They applied the QOI/QOS method to a target tracking example in which they generalized the end user's needs for QOI parameters from which the tracking system conferred the QOS capabilities over state and covariance information. Yu and Sycara [42] addressed the QOI in a distributed decision fusion system by learning the parameters. They applied the technique to determine the QOI information on target reliabilities (or better termed confidences) from a Dempster-Shafer method. Quality of information impacts fusion decisions [43].

Quality of Information is still an emerging topic as information is different for different users and systems. For example, QOI includes: Accuracy, Timeliness, Certainty, and Integrity [44]. QOI integrity measures whether the data has not been manipulated as it impacts the shared situational awareness [45].

Closely related to QOI, is *quality of service* (QOS) as it relates to the information flow and availability. QOS has been well vetted in the communications literature [46] as throughput, delay, error, and jitter.

QOI/QOS requires comparisons of:

Usability versus Usefulness
Accuracy versus Precision
Verification versus Validity

from which we address information gain, quality, and robustness, respectively. As MOPs come from rigorous standard metrics to determine such things as accuracy, there is a need for pragmatic metrics to determine the validity of information aggregation for useful decision making. In the next section we will look at the QOI literature that addresses issues of information service and type to advance the discussion in HLF metrics.

2.5 Metric Standardization

Standardization of HLF performance measures are needed not for research by the fusion community, but rather in the testing, evaluation, and transition of the technology to operational settings. Much work has been completed in addressing various research measures as they pertain to the LLF; however, formalizing a set of general metrics would aid a testing facility in HLF end-user requirements. Determining the critical performance measures can be determined from a couple points of view.

1) Users working with machines (user refinement)
2) Machines working with humans (displays)
3) Users emulating user needs (situational awareness)
4) Information fusion, data mining, sensor exploitation, etc., functions to afford human enhanced capabilities.

3 Information Fusion Quality Measures

To determine the contribution of any system, be it hardware or software, one has to test and evaluate the system. The evaluation can be conducted using either: 1) simulated data/simulated users, 2) simulated data/real users, or 3) real data/real users. The interchange between the information fusion performance and the user interest is based on the quality of the data. Blasch developed *Information Fusion Quality of Service* (QOS) *Measures* including timeliness, accuracy, confidence, throughput, and cost. Waltz and Llinas [5] listed timeliness, accuracy, and resolution. Others postulated *Quality of Information* (QOI) metrics, however, there is a large set of Information Quality Standards that still need to be leveraged.

Figure 2 illustrates an example of high-level needs as the user has many data bases available. Determining what is needed is as important as how good it is. The user requests decision-quality information at the correct time.

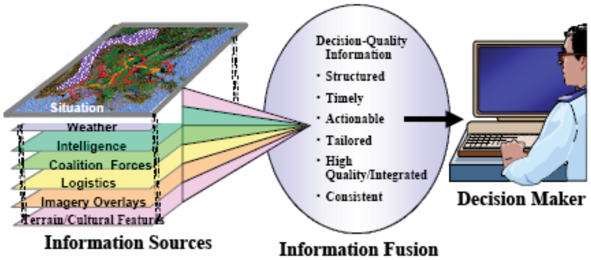

Figure 2. Information Fusion Decision Quality [47]

Next, we develop a relation between QOS and QOI.

3.1 Quality of Service

Information fusion provides a service to the user. Such issues as efficiency and effectiveness are important in delivering actionable information. To afford interactions between future IF designs and users *information needs*, metrics are required. The metrics chosen include timeliness, accuracy, throughput, confidence, and cost. These metrics are similar to the standard QoS metrics in communication theory and human factors literature, as shown in Table 2. [38]

Table 2: Metrics for various Disciplines.

COMM	User	Info Fusion	ATR/ID	TRACK
Delay	Reaction Time	**Timeliness**	Acquisition /Run Time	Update Rate
Probability of Error	Confidence	**Confidence**	Prob. (Hit), Prob. (FA)	Prob. of Detection
Delay Variation	Attention	**Accuracy**	Positional Accuracy	Covariance
Throughput	Workload	**Throughput**	No. Images	No. Targets
Cost	Cost	**Cost**	No. platforms	No. Assets

In addition to the metrics that establish the core quality (accuracy/integrity) of information, there are issues surrounding information security and quality.

3.2 Quality of Information

Quality of information (QOI) can be described either from the data itself or from the application. QOI from data is based on the accuracy, reliability, and confidence associated with the data. Typically, these "quality" measures are based on a probabilistic uncertainty, reliability confidence, and ignorance not to be confused with semantic uncertainty, reliability/availability in manufacturing, and incompleteness in possibilistic theory; respectively. Two groups developing QOI standards include the system management literature and the document retrieval literature for organizational effectiveness.

Additionally, QOI is based on the information suitability for a given task and can be subjective as relative to a specific user. For example, *Information quality assurance* is the process to guarantee confidence that particular information meets some context-specific quality requirements. A list of dimensions or elements used in assessing subjective *Information Quality* is: [48, 49]

- *Intrinsic IQ*: Accuracy, Objectivity, Believability, Reputation
- *Contextual IQ*: Relevancy, Value-Added, Timeliness, Completeness, Amount of information
- *Representational IQ*: Interpretability, Ease of understanding, Concise representation, Consistent representation
- *Accessibility IQ*: Accessibility, Access security

Additional measures include:

- *Authority* - expertise or recognized official status of a source such as the reputation of the author and publisher.
- *Scope of coverage* - extent to which a source explores a topic. Consider time periods, geography or jurisdiction and coverage of related or narrower topics.
- *Composition and Organization* - ability of the information source to present its particular message in a coherent, logically sequential manner.
- *Objectivity* - the bias or lack of bias expressed when a writer interprets or analyze facts. Consider the use of persuasive language, the source's presentation of other viewpoints, its reason for providing the information and advertising.
- *Integrity* - adherence to moral and ethical principles; soundness of moral character; the state of being whole, entire, or undiminished
- *Comprehensiveness*
    - 1. of large scope, inclusive: a comprehensive study.
    - 2. comprehending mentally: an extensive mental grasp.
    - 3. Insurance: providing broad protection against loss.
- *Validity* - degree of truthfulness of the information
- *Uniqueness* - originating point of the information but also the manner in which it is presented and thus the perception which it conjures.
- *Timeliness* - current at the time of publication. Consider publication, creation and revision dates.
- *Reproducibility* (utilized primarily when referring to instructive information): means that documented methods are capable of being used on the same data set to achieve a consistent result.

QOI has many purposes such as verification and validation.

Verification is a *Quality assurance process* that is used to evaluate whether or not a product, service, or system complies with regulations, specifications, or conditions imposed at the start of a development phase. Verification can be in development, scale-up, or production. Verification is often an internal process. It provides assurance that the product will fit certain quality standards and can be a measure of confidence.

Validation is *Quality control process* of establishing evidence (i.e. measuring and testing against the requirements) that a product, service, or system accomplishes its intended requirements. Validation often involves acceptance of fitness for purpose with end users and other product stakeholders.

Quality control and assurance can be derived from the measures of merit (MOM). MOMs are general goals for an IFS to obtain. Green [50] puts together this list of MOMs that could be useful for a HLF discussion (see Table 3). For instance, the user would advocate these desires from which a HLF system could calculate.

Table 3: Desired Characteristics of MOM

Characteristics	Definition
• Mission oriented	• Relates to force/system.
• Discriminatory	• Identifies real difference between alternatives.
• Measurable	• Can be computed or estimated.
• Quantitative	• Can be assigned numbers or ranked.
• Realistic	• Relates realistically to the C2 system and associated uncertainties.
• Objective	• Defined or derived, independent of subjective opinion (it is recognized that some measures cannot be objectively defined).
• Appropriate	• Relates to acceptable standards and analysis objectives.
• Sensitive	• Reflects changes in system variables.
• Inclusive	• Reflects those standards required by the analysis objectives.
• Independent	• Mutually exclusive with respect to other measures.
• Simple	• Easily understood by the user.

(From Green and Johnson, *Towards a Theory of Measures of Effectiveness*) [50]

4 Information Fusion MOEs

MOEs derive from MOMs and typical HLF metrics have been discussed in a military context. The fusion MOPs lead to MOEs to MOFEs. As IF is maturing, many new applications require a revisit to the general definitions.

4.1 Low-Level MOEs

There are groups developing MOEs for LLF tasks based on object data [51, 52] for military situations. Llinas [6] develops a mapping from LLF to measures of military effectiveness. Table 4 lists the various metrics and definitions that are useful for HLF discussion.

Table 4: Four Categories of Measures of Merit (From Llinas, Ch 20 [6])

Measure	Definition	Typical Examples
Measures of Force Effectiveness (MOFE)	Measure of how a C^3 system and the force of which it is a part perform military missions	Outcome of battle Cost of system Survivability Attrition rates Exchange ratio Weapons on targets
Measures of Effectiveness (MOE)	Measure of how a C^3 system performs its functions within an operational environment	Target nomination rate Timeliness of information Accuracy of information Warning time Target leakage Countermeasure immunity Communications survivability
Measures of Performance (MOP)	Measures related to dimensional parameters (both physical and structural) but measure attributes of system behavior	Detection probability False alarm rate Location estimate accuracy Target ID accuracy ID probability / range Communication time delay Sensor spatial coverage Time to detect
Dimensional Parameters	The properties or characteristics inherent in the physical entities whose values determine system behavior and the structure under question, even when not operating	Signal-to-noise ratio Bandwidth, frequency Operations per second Aperture dimensions Bit error rates Resolution Sample rates Anti-jamming margins Cost

For information fusion system performance analysis, we typically use measures of performance (MOP) to determine the system quality where some MOEs can be viewed as information quality (timeliness, accuracy). To determine effectiveness, we have to test the measures for *robustness* as well as the metric usefulness in HLF tasks.

4.2 High-Level MOEs

High level MOES can be viewed from the discussion of the MOM criteria needs as shown in Table 5.

Table 5: Criteria Measures (From Llinas Ch 20 [6])

Level 1 Criteria	Level 2, 3 Criteria
• Accuracy • Repeatability/consistency • Robustness • Computational complexity	• Correctness in reasoning • Quality of decisions/advice/ recommendations • Intelligent behavior • Adaptability in reasoning (robustness)

From Table 5, both quality and robustness are addressed with correctness and intelligence support decision making. Decision-making can be viewed as understanding in situational awareness as shown in Table 6.

Table 6: Situation Awareness [from 53]

		Phase	
		Process	Outcome
Goal	Tactical (Short Term)	Situation Assessment	Situation Awareness
Goal	Strategic (Long-Term)	Sense Making	Understanding

Using the definition of HLF, we can determine a summary set of metrics for situation, threat, and user assessment.

Table 7: High-Level MOEs

	Situation	Threat	User
MOFE	Comprehension	Survivability	Command
MOE	Awareness	Resilience	Timeliness
MOP	Detection	Risk Assessment	Actionable Information

4.3 Organizational Effectiveness

There are many ways to measure the effectiveness of an organization. Using an example of information systems functions, there are many ways to measure "effectiveness" such as such as quality, productivity, and efficiency [54]. A system provides information exchange with the environment to the organization (teams) through information processing, profitability, flexibility, and adaptability [55, 56]. Based on the thresholds and objectives of the test, we can determine the system capability to perform in the field. Testing the system and the organization in a real scenario is required to meet measures of objectives (MOOs).

Table 8: Testing Figure of Merit (FOM) Measures

FOM	**Simulated Data Simulated Tests**	**Real Data, Simulated Scenario**	**Real Data Live Scenario**
Performance *MOP*	Monte Carlo Tests	Trials	QOS/QOI Standards
Effectiveness *MOE*	Design of Experiments	Robustness	Actionable
Objectives *MOO*	Parameter Specifications	Thresholds	Measured Achievements

Sproles [57] discussed effectiveness evaluation issues. Such issues as real-world events [58] and culture [59] determine the efficacy of the system. However, there is a need for modeling [60] and system evaluation [61, 62].

In Section 3, we discussed quality measures and in Section 4, we discussed various effectiveness metrics; however, these metrics need to be tested to constitute robustness. Given the many references of HLF exemplar metrics, analysis, and discussion, one issue to address is whether or not there is an information fusion gain.

4.4 Information Gain

Information gain is the ability of the system to provide improvement – such as in a receiver operator curve [63, 64] or entropy analysis [65]. Das [34] describes a measure of effectiveness for decision trees using information gain. Within the above algorithm, a measure of effectiveness, called *information gain*, [34] of an attribute *A* is computed via the procedure *Gain*(*Training Set*, *A*). The attribute that provides the maximum information gain is placed at the root of the decision tree. The information gain metric is an information theoretic measure of how much "entropy" is revealed by a specific attribute. Given a collection *S* of *c* class labels, the entropy is defined as

$$Entropy\,(S) \;=- \sum_{i=1}^{c} p_{\,i} \operatorname{Log}_2 (p_{\,i})$$

where p_i is the proportion of *S* belonging to class *i*. The formula for computing information gain for an attribute *A* with respect to a set of instances *S* is

$$Gain(S, A) \;=\; Entropy(S) - \sum_{v \,\in\, \text{Values}(A)} \frac{|S_v|}{|S|} Entropy(S_v)$$

where the sum is taken over all possible values of the attribute *A*, and S_v is the subset of *A* for which the attribute *A* has the value *v*. Das gives an example to account for movement over various weather conditions (normal, rain, foggy), visibility (clear, poor), and mobility (move, slow, stop).

5 Situation Awareness Example

To determine a HLF MOE, we need to consider information gain, quality, and robustness.

InfoGain = value-added aggregation of elements of a situation (e.g. ability to link different regions of activity into a common temporal/spatial operational picture)
Quality = timeliness for actionable information, uncertainty reduction, and information confidence
Robustness = coping with real-world variation

Fusion Effectiveness = Info Gain * Quality * Robustness

Our example comes from a need to protect and address user needs to protect a coastal area [66, 67, 68]. Our example comes from the CanCoastWatch (CCW) testbed where Li, *et. al*. [69] looked at high-level data in a goal-driven net-enabled distributed data fusion system.

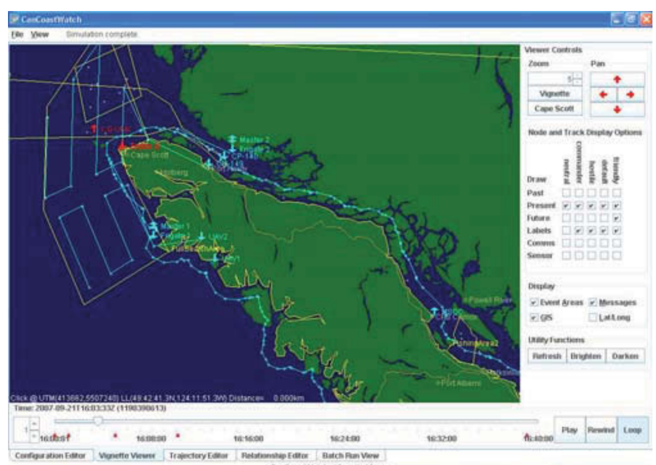

Figure 3. Example of Maritime Domain Awareness.

In the Maritime Domain Awareness system, the goal is to provide search and coverage of possible activities. Parameters used in the search include: search area, time of last visit, detections from radar, sonar and detections from video, and communication. Low level SAR, EO/IR, and radar information provide object track and ID information. The situational evidence is gathered from the commanders needs through goals. Observations provide the ability of a user to observe, orient, decide, and act over the track and ID information. Both the IFS and the user reasons over the situation and determines a level of confidence in the analysis.

Wehn *et. al.*, [70] looked at the decision function as related to planning and resource management. Goals were to evaluate the system effectiveness for net-enabled operations such as synchronization, scheduling, and search. Using the goals of HLF planning, effectiveness, and information content, we revisit the scenario with the general HLF metrics.

In a cooperative scenario, detected objects can be confirmed; however for the non-cooperative case, the detected objects cannot be communicated with. Our MOE includes information gain [IG] (confidence of track and ID information), information quality [IQ] (data fusion coverage area), and robustness (whether or not the information is consistent, or needs multiple verifications). Robustness can be repeated observations or confirmed through communication.

Table 9: Variables of HLF-MOE

IG	IQ	Robustness
Fusion of radar, Sonar and Video	Uncertainty with area covered	Repeated measurements

Using the search area, we wish (assuming the same number of measurements) to optimally utilize the sensors. We look at three scenarios where different data comes from 2 sensors. We calculate the information gain (same sensor with different looks), the quality of the data (as related to the sensor resolution as a measure of confidence), and robustness as a measure of consistency. Assuming that the system is robust (which could be better modeled with real-world data) we determine the effectiveness of the three approaches shown in Figure 4 in the high traffic areas (upper left of Figure 3).

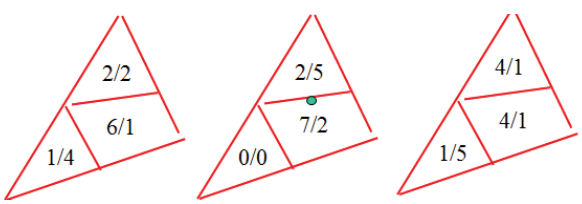

Figure 4. Information Gain Evaluation.

Case 1 (*Distributed approach*) shows that the high-resolution EO sensor (9 looks) is focused at the areas with more traffic, while the low-resolution radar (7 looks) looks at the periphery. Case 2 (*Focused approach*) only concentrates at the areas of traffic, discounted low probability information in the areas with less traffic. Finally, Case 3 (*Specialized approach*) partitions the sensor capabilities with the high-resolution sensor looking at the high dense areas, while the low-resolution sensor is scanning the areas with less traffic. Results are shown in Table 10.

Table 10: Results of MOE for SA

	Distributed	Focused	Specialized
Info Gain	0.23	0.18	0.29
Info Quality	0.68	0.85	0.625
Effectiveness	0.157	0.154	0.18

From this simple example, we see that the focused and distributed approaches give about the same effectiveness with a tradeoff in IG and IQ. One challenge in the focused approach is that the low-probability areas (which could be the areas the operators need the most help) are discounted. The specialized approach validates its effectiveness in that the best sensors are applied to the situations that they can monitor. The information gain is larger, which increases effectiveness since the same distribution of looks over similar quadrants yield about the same IQ. Thus, it is better to have a wider and specialized sampling to be more effective, which should be intuitive.

6 Conclusions

In order to address issues for HLF effectiveness, this paper brings together prior research to postulate a simplistic taxonomy to establish a discussion. Information fusion has determined a set of performance metrics for general tracking and ID; but a similar set of HLF MOE standards is needed. The QOI/QOS discussion is but one part of the overall user concerns for a usable system. For an IFS to be operational, there needs to be a verified information gain and validation of robustness over various situational operating conditions. In a simple scenario of the CanCoastWatch testbed, we simulated the case for effectiveness as a compiled from information gain, quality, and robustness parameters. We look forward to future discussions and will further refine the HLF MOE discussion with international standards.

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