E. P. Blasch, R. Breton, and P. Valin, "Information Fusion Measures of Effectiveness (MOE) for Decision Support," *Proc. SPIE* 8050, 2011.

Information Fusion Measures of Effectiveness (MOE) for Decision Support

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ABSTRACT

For decades, there have been discussions on measures of merits (MOM) that include measures of effectiveness (MOE) and measures of performance (MOP) for system-level performance. As the amount of sensed and collected data becomes increasingly large, there is a need to look at the architectures, metrics, and processes that provide the best methods for decision support systems. In this paper, we overview some information fusion methods in decision support and address the capability to measure the effects of the fusion products on user functions. The current standard Information Fusion model is the Data Fusion Information Group (DFIG) model that specifically addresses the needs of the user in an information fusion system. Decision support implies that information methods augment user decision making as opposed to the machine making the decision and displaying it to user. We develop a list of suggested measures of merits that facilitate decision support decision support **Measures of Effectiveness (MOE) metrics of quality, information gain, and robustness**, from the analysis based on the **measures of performance** (MOPs) of **timeliness, accuracy, confidence, throughput**, and **cost**. We demonstrate in an example with motion imagery to support the MOEs of quality (time/decision confidence plots), information gain (completeness of annotated imagery for situation awareness), and robustness through analysis of imagery over time and repeated looks for enhanced target identification confidence.

Keywords: Information Fusion, Situational Assessment, MOVINT, Measures of Effectiveness, Decision Support, Data Fusion Information Group Model

1. INTRODUCTION

Decision Support requires protocols for human interaction, definition of the tasks, and understanding of the technology. Decision support systems (DSS) [1] include computer-based information systems that support business and organizational activities, control of assets, and presentation of situational entities that are similar to operating conditions of targets, sensors, and the environment respectively [2]. DSS enables decision making through interactive knowledge-based algorithms based on the compilation of useful information from raw data, documents, personal interactions, and models. Three components of DSS include models, databases, and user interfaces. *Models* could be user mental models, sensor and target models, and environmental models. With the advent of the information age and the World Wide Web, a host of resources can be used to aid users in decision making through *databases*, historical records, and political interactions. The *user interface* provides the integrating component of knowledge-based systems with the operator which requires cognitive modeling, graphical interfaces, interactive and exploratory functions, and metrics of analysis.

To motivate the MOE developments for DSS, we map user interface to information gain (usability/completeness), the database resources to quality (timeliness/confidence), and repeatability to robustness (tracking). In this paper, we are concerned with the decision support **Measures of Effectiveness** (MOE) metrics of *quality*, *information gain*, and *robustness*, from the analysis based on the **measures of performance** (MOPs) of *timeliness*, *accuracy*, *confidence*, *throughput*, and *cost*. In [3], we postulated a general High Level Information Fusion (HLIF) MOE as:

Effectiveness = InfoGain * Quality * Robustness

The information gain includes not only the fusion products (e.g. confidence in analysis), but also the completeness of information and the interface design for usability. Quality is based on the quality of service (e.g. timeliness) and information quality (e.g. data/source credibility). Robustness is over the context and number of use cases that can be captured. To determine the MOE, we aggregate the confidence and timeliness information for a MOE analysis in target discrimination using the C-OODA model. Section 2 overviews the elements of decision support systems. Sections 3 and 4 discuss information fusion methods from the OODA (Observe, Orient, Decide, Act) models. Section 5 discusses metrics and Section 6 discusses an example of MOEs for decision making for wide-area motion imagery.

2. DECISION SUPPORT DEVELOPMENTS

Power **[4]** defines different decision-support system (DSS) types:

- A **communication-driven DSS** supports more than one person working on a shared task;
- A **data-driven DSS** or data-oriented DSS emphasizes access to and manipulation of time series data;
- A **document-driven DSS** manages, retrieves, and manipulates unstructured information in a variety of formats;
- A **knowledge-driven DSS** provides specialized problem-solving expertise stored as facts, rules, or procedures;
- A **model-driven DSS** emphasizes access to and manipulation of statistical, optimization, or simulation parameters to assist decision makers in analyzing a situation.

Some additional types of DSS we include are:

- A **task-driven DSS** focuses on specific tasks that are required (e.g. an image analyst annotating images);
- A **mission-driven DSS** captures the overall situational picture for commanders and teams.

The TRIAD model [5, 6, 7] identifies the interactions between the User (Human), Technology (Tool), and Function (Task) as shown in Figure 1. Designing the decision (or automated) support system tool enables task accomplishment such as observing, orienting, deciding, and acting. Human Factor specialists support the human-task analysis with a cognitive task analysis (CTA). A CTA identifies how the humans perceive the task, what strategies and resources are required to accomplish the task, and when are critical time constraints. Even with highly automated systems, the human has still a significant role to play in the execution of the task; however DSS methods can reduce the workload and time-to-decision through proper decision aids [8] and displays [9]. For a mission-driven DSS, a cognitive work analysis (CWA) is needed to look at those emotional, cultural, and political factors that affect the user's performance (e.g. scoring the image analyst on target assessment with or without complete contextual information).

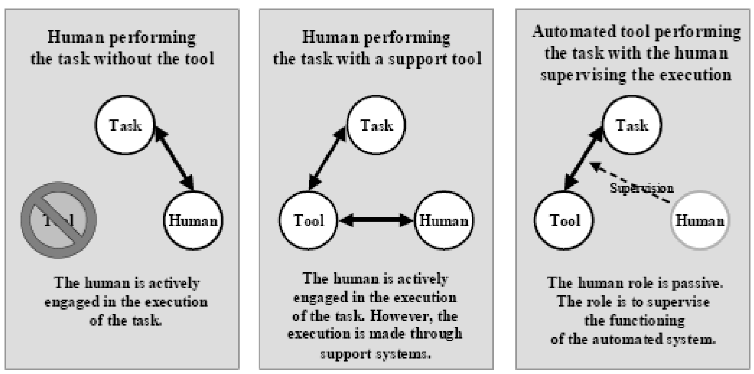

Figure 1. The Interaction between the Task, the Human and the Support or Automated Tool TRIAD.[5]

3. INFORMATION FUSION DECISION SUPPORT MODELING

3.1 DFIG Model

The *Data Fusion Information Group* (DFIG) process model (that replaces the JDL model) with its revisions and developments is shown in Figure 2 [10]. Management functions are divided into sensor control, platform placement, and user selection to meet mission objectives. Level 2 (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 which requires a DSS and cognitive modeling.

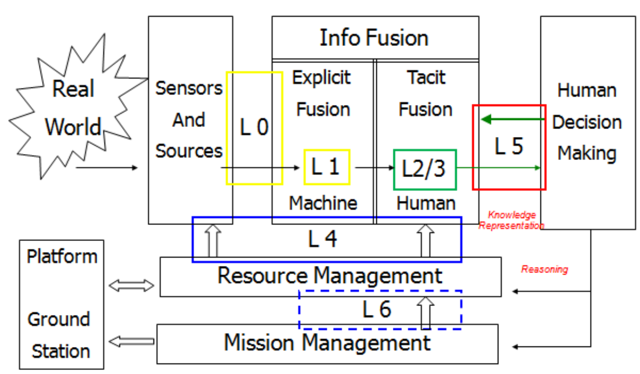

Figure 2. DFIG User-Fusion model [10].

3.2 OODA

One of the premier cognitive models for user decision-making is Boyd’s Observe, Orient, Decide Act (OODA) model, as shown in Figure 3. Figure 4 presents the cyclical nature of the OODA model in the context of the DFIG model.

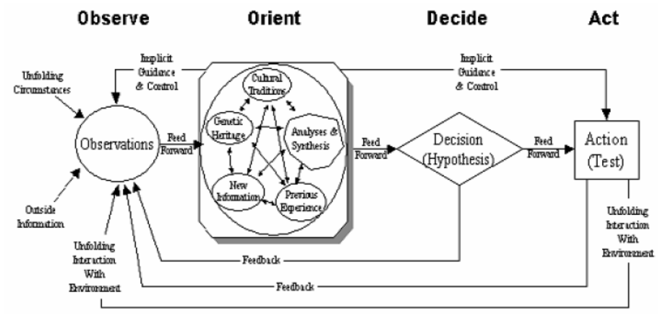

Figure 3. The extended OODA loop (Fadok, Boyd & Warden, 1995). [11]

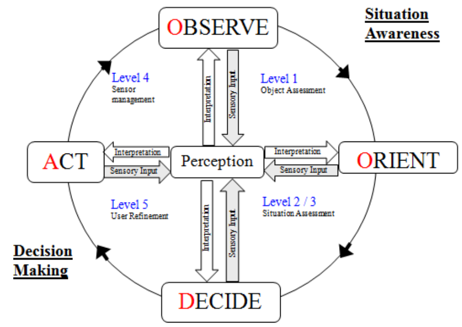

Figure 4. The OODA model in relation to the DFIG model.

The use of the OODA model has seen many developments and applications. The developments include the extended OODA [12], team T-OODA [13, 14, 15], the modular M-OODA [16, 17], the cognitive C-OODA [18, 19], and the Technology, Emotion, Culture, and Knowledge TECK-OODA [20]. The applications of the OODA include information fusion, military systems [21], target recognition [22], and cultural modeling [20]. Recently, the use of Level 5 fusion has been modeled for semi-automated decision making [23]. Key to the developments and instantiations of the OODA models include: application relevant decision-making based on context, time of analysis, and uncertainty analysis.

The OODA model is a cyclic process, evolving in the context of the analysis as shown in Figure 3. The traditional information fusion *data processing* functions (i.e. estimation) include: observe and orient which compose situation awareness. Numerous efforts have sought to model the evidence accumulation in providing a situational analysis including: perception of situations [24], presentation of object assessments [25], descriptions of situations [26], architectures of situational awareness [27], and user assessment of situations [28]. In duality, the information fusion *action* functions (i.e. control) include decide and act as the decision making processes. Examples of information fusion action analysis includes: decision making [29], user refinement [30], and sensor management [31].

The OODA model and DFIG model have similar properties to understand the decision process. When the user must reason over an enormous amount of data, for a contextual situation, and utilize reasoning, this requires a cognitive analysis of the situation. Cognitive models include the developments from physiology [32] to high-level information fusion [33]. Likewise, the cognitive aspects of course of actions require an analysis of the timeliness to reach a decision that can be acted upon. A comparison of the OODA model to the other information fusion models was analyzed in relation to the Omnibus model [34]. Table 1 compares the relevant information fusion decision making models from which we explore the cognitive (C-OODA) model as an extension to the Modular (M-OODA) model.

Table 1: Comparisons of Decision Making Models.

Activity	**DFIG Model**	**Omnibus Model**	**OODA**	**C-OODA**
Command Execution	Level 6	Resource Tasking	Act	Action Implementation
Decision Making	Level 5	Control	Decide	Action Selection
Sensor Management	Level 4	Decision Making		Select
Impact Assessment	Level 3	Context Processing	Orient	Understand
Situation Assessment	Level 2	Pattern Processing		
Object Assessment	Level 1	Feature Processing		
Signal/Info Processing	Level 0	Signal Processing	Observe	Sense
Data Acquisition/Registration		Sensing		Data Gathering

3.3 Modular OODA (M-OODA)

The M-OODA incorporates explicit control and flow components more in line with the current understanding of military command and control (C2) [16]. The M-OODA is based on a modular structure in which a module operates as a simple control system. A module is a task-goal directed activity formed of three core components.

The M-OODA model modifies the OODA loop based on the following principles:

1) It adopts a modular, or building blocks, approach in which each process of the OODA loop is represented as a generic module structured around three components: Process, State and Control;
2) It incorporates explicit control elements within and across modules enabling a bi-directional data/information flow between modules. It also includes a feedback loop within each module;
3) It provides a basic architecture for modeling a variety of team decision-making in the OODA loop.

To utilize the OODA concept in a C2 system, elements of the modules include: Data gathering (Observe), situational understanding (Orient), action selection (Decide), and action implementation (Act).

Table 2: Specifications of the core components of the M-OODA. [17]

Module	**Process**	**State**	**Control**
Data Gathering	Sense, encode, register, data translation, transduce, scan, fuse, detect, monitor	World representation, scene organization, multimodal integration	Vagueness, completeness, fuzziness, time available, quality of picture
Situation Understanding	Understand, identify, categorize, classify, organize, schematize	Mental model, schema, episode, familiarity estimation	Belief in interpretation, familiarity of schema, uncertainty on meaning
Action Selection	Select, choose, identify options, apply rules, consult, recognize, form hypothesis, simulate	Decision, list of actions (course of actions), risk evaluation, expected gain, selection rules	Risk assessment, completeness of options, cost assessment, gain estimation, familiarity of situation
Action Implementation	Act, planning, resource management, targeting, taking action	Set of Actions, schedule, milestones, plan, mission, orders	Feasibility, acceptability, resource availability

3.4 Cognitive OODA (C-OODA)

To support real-world decision making, a useful and accepted DSS tool must relate to standard systems (i.e. documents defining the armed forces doctrine on C2). Any C2 model has to keep explicit the high-level representation typical of the OODA loop. By formulating a detailed cognitively valid representation of the C2 decision cycle, the C-OODA (Cognitive-OODA) seeks to relate the user functions with their tools and tasks [17]. The C-OODA loop takes its roots in the classical version of the OODA loop and uses the modular architecture defined in the M-OODA loop proposed by Rousseau and Breton with key metrics of **uncertainty** and **timeliness**.

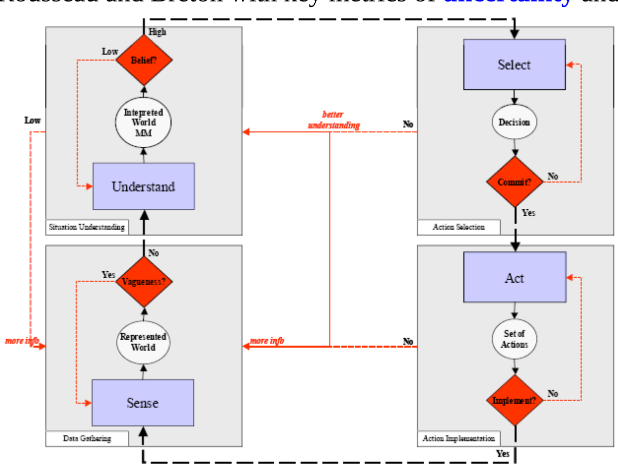

Figure 5. C-OODA Control modeling [17].

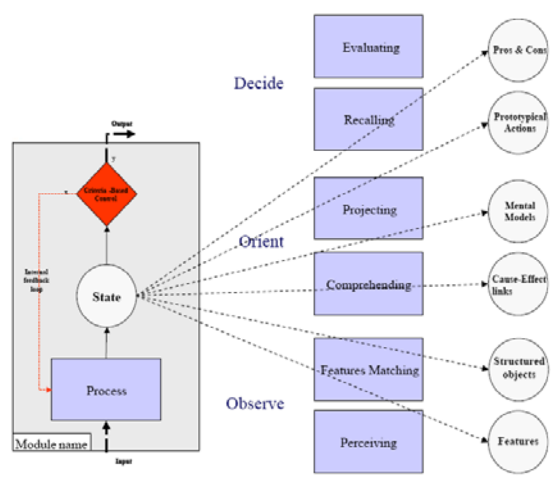

Figure 6. C-OODA Control modeling in relation to other models.

In order to show the functioning of the C-OODA loop, we define three different **decision-making situations**: Simple Match, Diagnosis and Evaluate Course of Action.

Simple Match: When the current situation is straightforward such that the crucial situation elements, the objectives, and the typical course of action to implement are easily recognized and identified.

Diagnosis: To cope with the presence of situation uncertainty, a DM cognitively attempts to establish relationships between events and causal factors in order to define, explain, and control the situation.

Evaluate Courses of Action: To augment data presentations, a mental simulation is required to evaluate potential difficulties, predict possible solutions and, consequently, to determine action implementations. Evaluation of COAs is called extended COA (ECOA) that require more elaborative processes which take time and resources.

3.5 TEAM DECISION MAKING

Within a given team, it is possible that different team members may work under more or less important time pressure; however the fusion of experts can work more productively through task specialization. An efficient team would be one that adequately allocates adequately the tasks among its team members based on their expertise, skills, and personality traits in order to reduce the workload, time pressure, and uncertainty factors. Breton *et. al*. [15] developed a taxonomy based on diversity of skills and time pressure which support C2 operations, as shown in Figure 7.

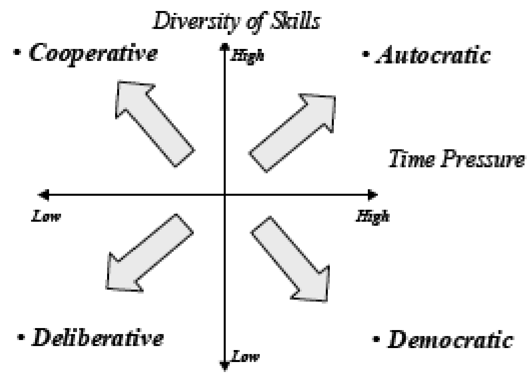

Figure 7. The illustrations of four team DM types.

- *Autocratic*: team leader, after obtaining all necessary information from the other team members, decides on a solution alone, without sharing the solution process.
- *Democratic*: different people analyze, consult, and vote on the situation and the best alternative which reduces the effect of human errors and biases.
- *Deliberative*: all team members share their thoughts and opinions on the situation in order to reach a consensus over the best solution as possible (e.g. jury). They may or may not be constrained by time.
- *Participative*: all team members share the problem, are involved in the generation and evaluation of potential solutions and reach a mutual agreement on the chosen solution.

These modes are similar to the User refinement behaviors of: neglect, consult, rely, and interact and over five basic functions of user refinement (1) Controlling, (2) Directing, (3) Coordinating, (4) Planning, and (5) Organizing [**35].**

4. INFORMATION FUSION DECISION SUPPORT

One example of information fusion decision support is data management for MOVINT (intelligence about a moving object). Typically object assessment algorithms track and identify the object to providing measures of performance (MOPs). MOPs support the measures of effectiveness, which can vary over the sensor types, environmental conditions, targets of interest, situational context, and users [36]. One example of MOVINT is detecting cars moving in an urban area [37]. Detecting traffic can be completed by fixed ground cameras or on dynamic UAVs. If the sensors are on UAVs, path planning is needed to route the UAVs to observe the traffic [38, 39] or to provide cooperation among UAVs [40]. Also, MOVINT can come from ground sensors such as that featured in the DARPA Grand Challenge [41] to orient [42] or classify or identify other targets [43, 44].

To facilitate target tracking and ID results [45] for decision support requires efforts in fusing imaging and non-imaging data [46, 47], understanding the user’s needs [48], the theoretical and knowledge models [49], and situational awareness processing techniques [50]. In a dynamic scenario, resource coordination [51] is needed for both context assessment, but also the ability to be aware of impending situational threats [52, 53]. For distributed sensing systems, to combine sensors, data, and user analysis requires pragmatic approaches to metrics [54, 55, 56].

Information fusion has been interested in the problems of databases for target trafficability (i.e. terrain information) [57], sensor management [58], and processing algorithms [59] from which to assess objects in the environment. Various techniques have incorporated grouping object movements [60], road information [61, 62], and updating the object states based on environmental constraints [63]. Detecting, classifying, identifying and tracking objects [64] has been important for a variety of sensors, including 2D visual, radar [65], and hyperspectral [66] data which support MOVINT.

Work on DSS metrics includes *tracking, sensor management*, and *target recognition* MOP metrics [67]. Information theoretic measures [68] and tracking analysis [69] can support the sensor and data management as well as determine the Information Quality and Quality of Service needs. MOPs provide decision support for situational awareness for command and control. Various other sources of soft data (human reports) can be combined with the hard (physics-based sensing) [70] to update the sensor management, placement, and reporting of the situation based on the context and the needs of users. For target recognition, a confusion matrix can be transformed into a receiver operator curve (ROC) [71].

4.1 Decision Support with OODA modeling for target recognition

Using Figure 8, the OODA loop models the object assessment system conducting automatic target recognition (ATR) which observes the sensor data and orients the information for the user. The user must decide if the ATR system is correct and act on the results. To continue the loop, the user tasks the ATR sensor to collect data for fusion evaluation. The human can cue the fusion system by: observation (perception), orientation (situation context), decision (comparisons), and action (selection of alternatives).

In Figure 8, (a) is the intersection of the ATR system and the user (where ATR is one of many fusion operations). The ATR ID confidence (1) must increase to enhance user trust, (2) represents the user tasking for more ATR data, and (3) shows that the OODA is iterated for efficiency (i.e. cycle time). We see that the human processes the observation and orientation information from fusion evaluation. The user looks at the fusion system outputs and determines the final decision of the target type and the action to be performed. The user-fusion system performance is typically evaluated with a receiver operator curve (ROC) which assesses the probability of detection (P_D) to various set of Probability of False alarms (P_{FA}). For the differing DM timing modes, we would be willing to operate on differing locations on the ROC curve. Figure 8 (b) shows the time window modes associated with multiple DM modes for action. For the reactive mode (e.g. autocratic), since the time window is immediate, the ATR P_D decision can accept a large P_{FA}. For the proactive mode (e.g. democratic), since anticipated threats are being assessed, it would be more important to lessen P_{FA}. Finally for the preventative mode (e.g. deliberative and participative team DM), we must ensure that the intentions are well substantiated in order to act, which would require a very low P_{FA}.

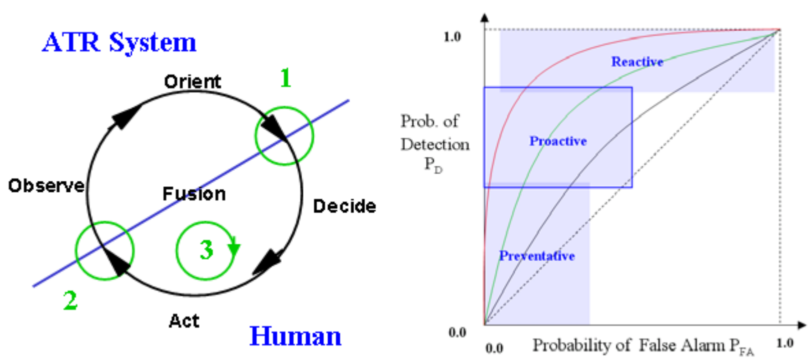

Figure 8. (a) An ATR-Human OODA timing control Loops and (b) the ROC detection analysis.

4.2 Test and Evaluation of Decision Support Systems

Decision support requires testing and analysis in real and virtual simulations. To provide a virtual test of a DSS, we need to capture the tasks over real world data. Through an evaluation analysis (Figure 9), we can implement, test, and demonstrate an improved exploitation workflow for exploitation systems, increase the use of machine automation to manage the production of intelligence from large volumes of persistent surveillance data, and perform forensic processing to support analysts and decision makers. With the advent of DSS technologies, there is a need to assess the capabilities (coverage analysis, robustness, and process flow) that enable effective usability

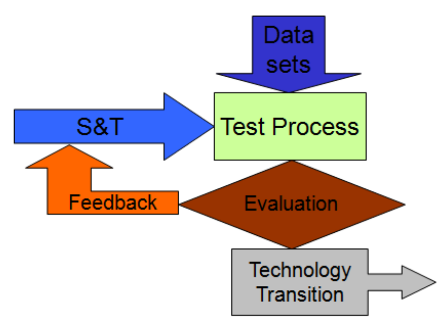

Figure 9. Test Process emphasizing the need for validated data sets and evaluation.

of the fusion techniques. For the transition process from science and technology (S & T) sensor design and algorithm exploration, there needs to be an appropriate test process in place to afford evaluation, shown in Figure 9. The test process includes the available training data for empirical analysis, theoretical models for predictive capabilities, and real-world demos to evaluate the robustness of the techniques. Demonstrations ground the DSS analysis and ensure that potential solutions are assessed and unanticipated challenges are discovered. The goal is to identify, measure, resolve, and minimize the extent to which data issues impact user functions through demonstration and experimentation studies. For example, DSS issues are present in (1) processing DSS technologies in a tactical environment that supports near-real-time decision making and (2) automated forensic processing to exploit vast quantities of data with minimal human intervention. For *tactical decision making*, the DSS issues surround providing the right data at the right time and with available ancillary information from which to make a decision. For *strategic forensic processing*, the timeline of information needs is more relaxed, putting more of the need of the DSS to explore multiple scenarios, mine for data that is relevant, and provide information updates that capture strategic options.

4.3 Structured and Unstructured Data Management Metrics of Effectiveness

Because effective DSS must incorporate diverse data structures it is important that a DSS address concerns of unstructured data in addition to structured data. Unstructured data (versus) structured data refers to computerized information that does not have a data structure (i.e. exists within a database). Examples of “unstructured data” may include (1) textual: documents, presentations, spreadsheets, annotated images, etc., (2) imagery: multimedia files, streaming video, etc., (3) HUMINT: reports, audio files, gestures, (4) sensors: seismic, acoustic, magnetic, radar, sonar, etc., and (5) environmental: weather, GIS, etc. [72]. All of the data has to be collected, acquired, exploited, stored, recalled, and tagged, not to mention a host of other activities. Most of data that is collected has some structure; however, for information fusion the inherent structure is not common among entities.

Processing of large volumes of data for DSS requires metrics, architectural models, and operational realistic scenarios to test data search, access, and dissemination [73]. Data exchange is an important area of information management that aims at understanding and developing foundations, methods, and algorithms for transferring data between differently structured information spaces to be used for diverse purposes over a networked environment [74]. Efficient and effective exchange of data must address many issues beyond just getting the data to where it is needed (transport) but also the ontologies [75] and protocols used. Issues of *dissemination* (access, availability, and control), *quality* (truth, relevance, and accuracy), *timeliness* (speed-to-need and information lifecycle) are challenges that fall under the data exchange scope of activity. Many of these metrics translate directly to decision outcomes (timeliness, user confidence, and accuracy). From a large data perspective, the process of data exchange is complicated by limitations in *interoperability*, diversity in applications and contexts, and even by the structure of the data itself.

A summary of ten key requirements that support measures of effectiveness include [76]:

- *Visibility*: Illustration such as folders and plots
- *Control*: Test, push, and pull of information
- *Auditing*: Complete and searchable
- *Security*: Data permissions and access
- *Performance*: communication and traffic flow
- *Scale*: amount of data
- *Ease of Installation*: timeliness of submission
- *Ease of Use*: distributed and timely access
- *Ease of Integration*: interoperability
- *Cost of Ownership*: money and effort

These methods are similar to the **QOS/IQ information fusion** standard metrics such as timeliness, accuracy, confidence, throughput, and cost; with most of the efforts in DSS focusing on throughput and timeliness. It is hard to judge the quality of information stored; however, a user can input this information when the data is sent to be archived.

Data maintenance is akin to equipment maintenance. In the case that equipment maintenance includes reliability, survivability, reparability, supportability, and other “ilities”; the same case can be made for decision support systems.

(1) *Reliability* is that the data is available, correct, and timely. Much of the use of the data is based on the need for the data and information at the correct time. To ensure data reliability means that it has to be stored and accessed in such a way that it can be retrieved.

(2) *Survivability*. The data needs to be collected and correlated with the pedigree on the data collection and decision making processing. To ensure that the data is available, it needs to “survive” in the database from which it is correctly called when needed, has the correct security labels, and is tagged in space, time, and events.

(3) *Supportability*: The data needs to have the associated contextual metadata information to be able to register, exploit, and fuse the data with other sources. Such aspects of formats, protocols, models will enable usability and effectiveness of the data.

We highlight one example from the above for reliability.

5. CONFIDENCE VERSUS RELIABILITY

To determine how to measure confidence for decision support, we need to look at formal definitions from STANAG 2022. Typically, reliability refers to the continuous operation of equipment. In most cases, the use of reliability for decision support refers to the equipment function; however for sensor management (or target classification), reliability can be confused with confidence as per the NATO Standardized Agreements [77, 78, 79].

STANAG 2022: Intelligence Reports
STANAG 4171: Allied Reliability and Maintainability Publications
STANAG 4158: Guidelines for Classifying Incidents for Reliability Estimation of Tracked and Wheeled Vehicles
STANAG 4626: Modular and Open Avionics Architectures

Credibility provides a soft definition of target identification which is closely related to reliability of which all the definitions are variations of "confidence" as shown below. Note that the MIL-STD-6040 provides quantitative labels.

RELIABILITY	**CODE**	**EXPLANATION From STANAG 2022**
Completely Reliable	A	A tried and trusted source which can be depended upon with ***confidence***
Usually Reliable	B	A past successful source for which there is still some element of doubt in particular cases
Fairly Reliable	C	A past occasionally used source upon which some degree of confidence can be based
Not Usually Reliable	D	A source which has been used in the past but has proved more often than not unreliable
Unreliable	E	A source which has been used in the past and has proved unworthy of any confidence
Cannot be judged	F	It refers to a source which has not been used in the past

CREDIBILITY	**CODE**	**EXPLANATION From STANAG 2022**
Confirmed	1	If it can be stated with ***certainty*** that the reported information originates from another source than the already existing information on the same object
Probably true	2	If the independence of the source cannot be guaranteed, but if, from the quantity and quality of previous reports, its ***likelihood*** is nevertheless regarded as sufficiently established
Possibly true	3	If insufficient confirmation to establish any higher degree of likelihood, a freshly reported item of information ***does not conflict*** with the previously reported target behavior
Doubtful	4	An item of information which tends to ***conflict*** with the previously reported or establish behavior pattern of an intelligence target
Improbable	5	An item of information which positively ***contradicts*** previously reported information of conflicts with the established behavior pattern of an intelligence target in a marked degree
Cannot be judged	6	If its truth cannot be judged

RELIABILITY OF INFO	**Code**	**Explanation from MIL-STD-6040**	**Value**
Highly/ Consistently reliable	A	Refers to information that can be depended upon with much **confidence**	0.95
Very reliable	B	Refers to information upon which some degree of confidence can be placed	0.85
Fairly reliable	C	Refers to information for which there is some element of doubt	0.75
Cannot be judged	F	Refers to information that has not yet been evaluated for reliability	0.60
Not Usually Reliable	D	Refers to information for which there is more doubt than confidence	0.40
Unreliable	E	Refers to information that has proven to unworthy of confidence	0.10

RELIABILITY OF Source	**Code**	**Explanation from MIL-STD-6040**	**Value**
ROS 100%	100	A tried and trusted source which can be depended upon with confidence	1.00
ROS 80%	80	A successful past source for which there is still some use-case element of doubt	0.80
ROS 60%	60	A past source upon which some degree of confidence can be tested.	0.60
ROS 40%	40	A past source has proved more often than not unreliable	0.40
ROS 20%	20	A past source has proved unworthy of any confidence	0.20
ROS 00%	0	A source which has not been used in the past	0.00

6. EXAMPLE OF DECISION SUPPORT FOR IMAGE ANALYST FUNCTIONS

To facilitate research in MOVINT, the Columbus Large Image Format (CLIF) Data was collected by deploying a distributed set of sensors to monitor, track, and classify vehicles [80] which includes a list of challenge problems such as joint data management (JDM) for data-to-decisions (D2D) [81]. In this example, we use the results collected and analyzed over the CLIF data to analyze a DSS for an Image Analyst.

6.1 User functions in a Decision Support System for MOVINT Targeting

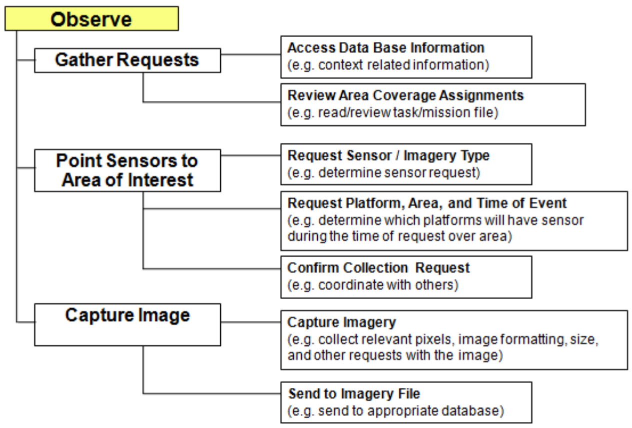

Figure 10. Observe and Orient Functions.

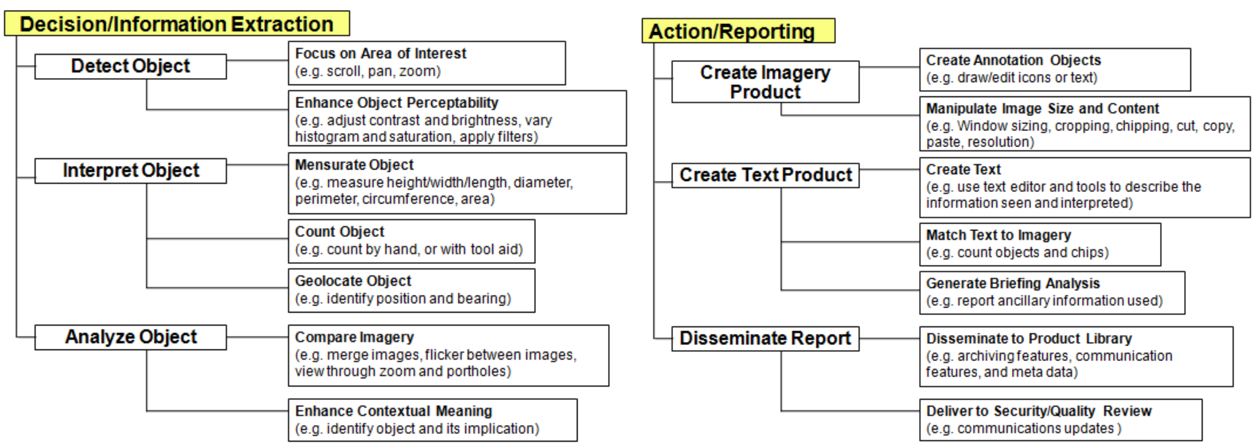

Figure 11. Decide and Act Functions.

The goal was to simulate the actions above for Decision Support.

6.2 MOVINT Decision Support and Confidence-Timeliness Plots

Visual analytics provide methods to visualize the data and analysis over MOVINT capabilities. MOVINT provides both tactical and operational intelligence (situational awareness) of the dynamic environment. For the operational analysis, we can provide a track presentation of the objects. For the CLIF data set, the truth information is available with the data history. Figure 12 presents displays of annotated targets in the image from different trackers including the *Bounded Particle Resampling L1* (L1-BPR) tracker [82, 83] and other methods described in [84]. The right plot shows the case of target detection over the four trackers in which the user is getting the information for MOVINT decision support.

To determine MOEs for DSS, we present the target confidence from classification fusion and accurate location information of the MOVINT results for **Information Gain**. Also, the information timeliness is an example of a **Quality** of Service attribute, while the imagery details the data quality. Finally, for **robustness**, we present different multiple tracker results process over a variety of operating conditions (OCs). Figure 12 shows the results, from which a user can determine not only the location of the object, but the key aspects of the MOVINT target features for positive identification. The Decision Support Measure of Effectiveness is the combined results of InfoGain, Quality, and Robustness that we are currently displaying to the operator.

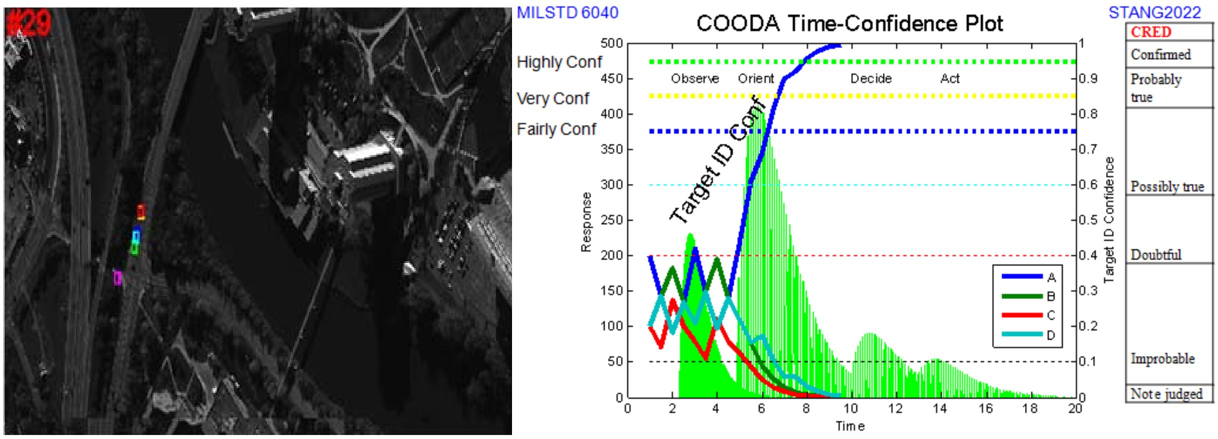

Figure 12. (*Left*) Annotated feature analysis using different tracking results and (*right*) the Decision Support Timeliness-Confidence Plot reporting from cumulated measurements in an OODA time analysis.

7. CONCLUSIONS

We have explored measures of effectiveness methods for Decision Support Systems (DSS) for information fusion focusing on MOVINT data-to-decision making. We showed that the DSS MOE metrics aggregate MOPs of (target accuracy and false alarm reduction) for enhanced and timely decision making through the C-OODA model. Improved exploitation workflow analysis needs to be evaluated within the context of the associated layered sensing assets, the exploitation tools, and the joint data management process. Many DSS processes are developed in virtual environments with simulated data. With the algorithms developed, a virtual experiment will be conducted with real humans and simulated data. Finally, human analysts (i.e. commanders and users) should be included in field trials to demonstrate and quantify the impact of various automation techniques on intelligence production improvements from DSS technologies.

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