IEEE Workshop on Object-Oriented, Real-time, Dependable Systems (WORDS 2003F),
1-3 Oct. 2003. Anacapri, Italy

Enhancing Dependability of the Battlefield Single Integrated Picture through Metrics for Modeling and Simulation of Time-Critical Scenarios

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Abstract

This paper presents a report of an ongoing research project to test and evaluate temporal and other dependability properties of the battlefield single integrated picture (SIP). It explores modeling and simulations of information flows in the battlespace with a view toward enhancing the SIP. The main emphasis will be on level-one data fusion, i.e. detection, identification and tracking of platforms and classifying them as friendly, neutral or hostile. Thus, the study will focus on metrics that pertain directly to the flow of relevant information in the battlespace during the time period of a particular target-classification task, and the dependability of that information.

Keywords – Data fusion, dependability, Force-Net, metrics, sensors, single integrated picture, time-criticality

1. Introduction

The purpose of this paper is to report an ongoing research project to test and evaluate properties of battlefield single integrated picture (SIP) that are associated with dependability and time criticality. In general, dependability includes accuracy, safety, security, fault tolerance, confidence, completeness, consistency, timeliness, and availability. For the purpose of this modeling and simulation (M&S) study, dependability will be determined by simulating data sets of independent variables, including latencies, and analyzing the statistical results.

This work supports ForceNet, which is the operational construct and architectural framework for naval warfare in the information age. [3]. The goal of ForceNet is to integrate warriors, sensors, command and control, platforms, and weapons into a networked, distributed combat force [3]. Part of Force-Net's plan is to increase sensor coverage [5].

M&S provide a preliminary means to test methods and concepts without conducting costly field trials. M&S can suggest efficient field tests that focus on specific problem areas. M&S trials can provide a cost-saving tool. However, it does not replace all field tests; it just allows researchers to limit the field tests to those that are most likely to yield a successful outcome.

Our focus is on the data available at the message level of granularity, with a view toward measuring and modeling the value added of process automation in the building of the SIP. We identify a few metrics that can enhance human understanding rather than to focus on the metrics associated, for example, with the absolute accuracy of each sensor. We select metrics to enable a tractable analysis of data from a simulation for level-one data fusion that will characterize the dependability of a SIP. Level-one data fusion is defined as the fusion of data related to detection, tracking, classification and the identification of platforms. (See, for example, [8]).

The paper is organized as follows. Section 2 explores the concept of a SIP as it relates to this study. Section 3 describes criteria to define the scope of this study. Section 4 covers characteristics of metrics. Section 5 covers time criticality. Section 6 describes the methodology, variables, and assumptions of the simulation. Section 7 covers the

Report Documentation Page

Form Approved
OMB No. 0704-0188

1. REPORT DATE	2. REPORT TYPE	3. DATES COVERED
03 OCT 2003	**N/A**	**-**

4. TITLE AND SUBTITLE
Enhancing Dependability of the Battlefield Single Integrated Picture through Metrics for Modeling and Simulation of Time-Critical Scenarios

5a. CONTRACT NUMBER

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)
Marion G. Ceruti, Joan L. Kaina

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
SSC Pacific San Diego, CA 92152-5001

8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)

10. SPONSOR/MONITOR'S ACRONYM(S)

11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release, distribution unlimited

13. SUPPLEMENTARY NOTES

14. ABSTRACT
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15. SUBJECT TERMS
Data fusion, dependability, Force-Net, metrics, sensors, single integrated picture, time-criticality

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	b. ABSTRACT	c. THIS PAGE			
unclassified	**unclassified**	**unclassified**	**UU**	**8**	

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std Z39-18

generation of input data sets for the simulation. Section 8 briefly covers the status of the model-evaluation effort. Section 9 suggests directions for future research.

2. Single integrated picture

A general definition of the SIP is "timely, fused, accurate, scalable, and reliable information from the entire battlespace (and) area of operations – undersea surface, ground, air, and cyberspace – maintained within realistic, combat-driven timelines that can be tailored to meet the mission-planning, execution, and assessment needs of each user" [7].

The definition stated above is consistent with the more specialized definition of SIP that will be used in this study. Here, the SIP is defined on an event-by-event basis using a tailored data set that will include only the data relevant to the task or event under consideration. This will exclude large quantities of irrelevant data that could obscure in noise the salient features of each classification task. In the simulation, data will be considered only if they are 1. available within a limited time period and 2. germane to each specific target-classification event.

For this study, such a data set, along with its metadata will be considered to constitute the SIP for that event. A comprehensive SIP of the battle space can be constructed for longer time periods by aggregating and summarizing the information that pertains to the events that occur during the time period.

3. Criteria to define scope

The selection of metrics for an M&S project is very important to the success of the effort. Ideally, the metrics selected should lead to a useful result that provides relevant information that can be translated into practical applications. Of the metrics that appear to be desirable, one must select the metrics that actually can be measured or reasonably estimated with some degree of realism and tractability. Measuring time intervals, enumerating events, specifying event sequences, and counting the number of data elements in a data cluster are all metrics that fall into this category.

The ability to simulate an event or scenario does not imply that the results necessarily will be realistic or accurate. Therefore any approach to this problem must consider the tradeoff between realism and tractability. Metrics will be considered if they are both desirable and tractable, and if they pertain directly to the flow of relevant information in the battlespace during the time period of a particular target-classification task.

The following criteria will be used to select metrics for this study, including measures of effectiveness (MOE) and measures of performance (MOP):

- Desirability of application,
- Tractability for M&S,
- Validity of comparison between M&S results and operationally measurable quantity,
- Relevance to the SIP,
- Temporal factors, such as latencies that pertain to time-critical scenarios.

To maintain the study within the realm of tractability, we will limit the scope to cover aspects of the SIP with regard to level-one fusion, which includes target detection, localization and classification. Therefore, problems in the following domains normally associated with battlespace-information systems are considered outside the scope of this study and will not be addressed:

- Communications in networks,
- Data elements below message-level granularity,
- Fusion algorithms and models that process data at the voltage level of sensor functionality,
- Raw data from sensor arrays,
- Image analysis at the pixel vs. feature level.

The focus of this study is on existing sensors and message data from existing communication systems rather than on exploratory development.

No single authority controls all sensors because communities that administer the various sensor types each have developed independently their own methods of operation. Therefore, sensors operate in a decentralized, distributed manner. No one regulates the overall amount of data produced across sensor types. This creates a situation of information overload for sensor-data analysts and command-center personnel, among all the other challenges of sensor-data fusion. As a result, we do not have the capacity to analyze in every way all of the data from all sensors at our disposal, especially when such an analysis involves heterogeneous sensor types (e.g. acoustic and imagery).

Given that this is the case, selecting data that will be the most useful to battlefield commanders is very important. Until now, few studies have been completed to characterize data flow in the battlefield with the goal of finding better ways to use the data from these existing sensors.

General fusion of sensor-data sets of arbitrary size is an NP-complete problem. However this study is predicated on the premise that sensor-fusion metrics and the application of the appropriate models can provide heuristics to reduce the complexity of the problem into the realm of tractability.

4. Metrics characteristics

Design issues associated with metrics must be addressed before starting the design of test-data sets.

In this simulation, we will control independent variables such as the sensor data-fusion schemata, data-element-cluster size, cluster-formation latency, fusion latency, and information pedigree that contribute to the SIP.

We will input these data sets into one or more models that relate the independent variables to performance on target classification tasks in which a platform is identified as friendly, neutral, or hostile. We will collect statistics suitable for receiver-operator characteristics (ROC) analysis. These statistics are hits (H), missed targets (M), correct rejections (CR) and false alarms (FA). Metrics for latencies also will be important here, as they relate to time-critical events. Metrics useful in level-one fusion include probability of detection (P(d)), false-alarm rate (FAR), probability of correct identification P(CID). These probabilities can be generated from H, M, CR and FA.

In general, different metrics pertain to different aspects of dependability. Metrics provide a means to measure some aspects of dependability and provide some evidence that a fusion methodology is improving over time. Thus, H and M as defined above constitute MOPs.

Various dimensions associated with metrics include aspects and characteristics of MOEs. MOPs are the interactions between these dimensions and aspects, as well as the metrics themselves. Many MOPs may contribute to a single MOE. For example, consider the MOE, "Determine the ability to recognize and react to theater air and missile threats." A contributing MOP is "Number of hostile aircraft and missiles that penetrate friendly theatre defenses compared to total number of threat presentation (% successful threat penetrations.)"

Our dependent variables represent MOPs. In this example, one MOP could be the number of missed airborne targets counted in a given section of air space. Thus, an overall MOE such as the missed-target rate for the battle can be generated.

The aspects of metrics used for M&S can be categorized according to several factors as follows.

• Metrics must pertain to level-one data fusion.
• Quantitative vs. subjective - For example, a distance is a directly measurable quantity whereas combat readiness is a quality that depends at least partially on subjective judgement.
• Deterministic vs. stochastic – The measurement of latencies, for example, is deterministic whereas the collection of data for ROC analysis relies on statistics based on many observations.
• Accuracy and timeliness – Measures of timeliness must be developed to assist evaluation of when to ignore data that have become outdated. The use of outdated quantities may lead to inaccurate results. A measure of timeliness will need to take into account the time criticality of the scenario (See section 5.)
• Theoretical vs. empirical or pragmatic – Some metrics have a sound basis in theory whereas others may be used simply because they predict events without necessarily knowing the reason why.
• Conditions of usage. Some metrics pertain to sensors that work best in clear weather and others may be just as effective in bad weather. This can be summarized in the metadata.
• Consider tests of ablation – If a sensor's input, i.e. a data element in a fusion cluster is omitted, will this have an impact on the results? Such tests can be resource intensive if conducted in the field, but a simulation should be able to increase the efficiency by an order of magnitude.
• Consider that a metric may consist of two parts, the desired goal and a minimum acceptable value.

5. Time criticality

The SIP changes frequently. The faster the OPTEMPO of the battle, the faster it changes. As time-critical events emerge in the battlespace, so evolves the requirement to reduce data collection and processing time to meet emerging readiness requirements in real time. Therefore, inextricably tied to the notion of SIP in a battlespace is the notion of time criticality (TC), a definition for which has been offered in [2]. Two approaches to TC will be considered in this study. One is to ignore how metrics may be used in real time and approach metrics with the idea of evaluating factors in an analytical mode.

The other way to approach metrics TC is to evaluate their usefulness in an operational scenario, in which case, we can apply metric evaluations in a decision mode where the time to evaluate the metric can occur within the timeframe of a time-critical horizon. In M&S, tradeoffs can be explored with respect to this use of metrics. The usefulness of metrics in the operational decision mode will depend not only on value added but also on the efficiency of application. Each metric needs to be evaluated vis-à-vis how it affects TC and how the time-critical nature of the situation will least indicate the metrics that should be used at each stage of the analysis. Thus, the time to calculate, measure, or estimate each metric will be compared to the time to determine if using this metric is realistic given time constraints.

6. Approach and methodology

Threat assessments and real-time responses today depend on fusing data from disparate sources. Data arrive in different message types at different times into a command center where the SIP is being formulated, monitored, and updated constantly. One metric is the latency between the arrival time of a full data set and updates to the data set. Latency between SIP updates and action to engage targets is another latency that can be simulated and measured.

In this simulation, initially, we will use metrics such as time measurements of latencies, statistics, and counting objects, such as data elements, fusion graphic structures (called schemata), and measures of the completeness of the SIP. The time between receipt of data and action to engage targets is another metric that could be useful to evaluate the utility for use in operational scenarios. However, this would need to be evaluated over many simulated tests.

A Receiver Operator Characteristics (ROC) analysis can be performed on data collected from evaluating the outcomes of a series of target classification tasks, i.e. the dependent variables. The processed data resulting from calculating statistics that summarize these outcomes, i.e. the values of the dependent variables include the following:

a. Hits (Example: correct classification of hostile or friendly platform, Se = Co),
b. Missed targets (Example: failure to identify hostile platform, Se ≠ Co),
c. False alarms (Example: classification of neutral or friendly platform as hostile, Se ≠ Co),
d. Correct rejections (Example: correct classification of neutral platforms, Se = Co).

The traditional receiver-operator characteristics (ROC) analysis need to be modified to account for the three-value case that includes the alternatives of hostile, neutral and friendly. (See section 6.4.)

6.1 Assumptions & definition of variables

To simplify the scenario, we assume that the independent variables for a simulation define the SIP on a task-by-task basis. This reduces the number of data elements that need to be considered for each target ID to the set of data that directly pertain to the task. Thus, for the purpose of this simulation study a small number of data elements can be present. This is the set of data elements necessary to classify or identify the target. This set is assumed for simplicity to contain fewer data elements than the total required for an actual case. We consider also the number of data elements available to make the Identification Friend Foe (IFF) determination. Examples of data elements are a frequency, pulse repetition rate, platform latitude, longitude, depth, altitude, and platform heading.

Let Nr be the ideal cluster size, i.e. the number of data elements that need to be present simultaneously for a positive identification and/or classification. Thus, Nr will be a small number that will be selected for tractability for the purpose of generating the simulation, excluding the trivial case of Nr = 1. When the simulation is well established and positive results have been obtained, Nr can be increased to a more realistic number used in actual fusion tasks.

Similarly, Nt is defined as the size of the actual data cluster at time t, i.e. the number of relevant data elements actually present in an information base at time, t, where t is assumed to be the time when fusion starts. Nt is either a subset of Nr, or, equal to Nr in a best-case situation. For this study, the information base consists of a collection of data sources, such as knowledge bases, databases, messages, intelligence reports, and visual observations that can be captured as data, sent in messages, and introduced into the fusion process. Given these definitions, we can define the “completeness” of the single-integrated picture on a case-by-case basis as follows: Pc = Nt / Nr. Thus, if the raw data set is complete, Pc = 1.

We consider only pair-wise data fusion and ignore any fusion algorithm that requires an input of three or more data elements simultaneously. For example, with a maximum Nr of 6, this implies a maximum of five successive pair-wise fusion steps. Three-way fusion and higher clusters result in more complicated fusion schemata. They can be considered in a future project when the simulation of pair-wise fusion is understood better and has been proven to be tractable.

The independent variables include raw data-set size (Nt), ideal raw data-set size (Nr), fusion schema, and fusion latency. The dependent variables include target hits (H), missed targets (M), false alarms (FA), and correct rejections (CR) described above. These variables lend themselves well to ROC analysis. One can define a set of H, M, CR, and FA for target classification and another set for target identification. Target classification is the determination of the category of a platform, where the choices are hostile, neutral and friendly. Target identification is the determination of the exact identity of a platform, such as the name and/or hull number of a specific vessel, or the number on the fuselage of a specific aircraft.

6.2 Fusion schemata and latencies

The graphic fusion schemata for each target ID task and its latencies must be characterized. For example, the latency during which data clusters are formed, tc, is defined as the time that the last data element is received minus the time that the second element was received. (N.B. Data "groups" of size, N = 1, are not considered because they are not clusters.)

Similarly, td can be defined as the "delay latency" between cluster formation and the onset of fusion.

Lastly, the fusion time, tf, is the time between fusion onset and the completion of the fusion process. For fusion schemata with multiple fusion steps, tf will be the sum of the latencies for all linear steps for the longest fusion chain (i.e. the section of the schema with the limiting factor). This excludes shorter (i.e. faster) branches of the fusion chain that occur in parallel. In practice, tf can include the time interval represented by tc because fusion can begin before the data cluster is entirely formed. If this is the case, tc is included in, and entirely subsumed into tf.

In practice, tf will depend on the fusion algorithm as well as the input data. However, for the purpose of this study, tf will be varied to simulate the execution times of various fusion algorithms.

6.3 Examples of schemata

Two-variable schema. The smallest allowable cluster is Nt = 2. This allows, at most, one pair-wise fusion between two variables, A and B, which can be represented as graph nodes that can take values of "raw data elements." (N.B. For Nr = 2, Nt can be 1 or 2, but we ignore the trivial case of 1.) F1 is another graph node that represents the result of a fusion between A and B. The pair formed by values of A and B when they are used together is called a "raw data pair." F1 is not a variable that represents a raw data element because it is the result of fusion between A and B. F1, however, can participate in a fusion event with another raw data element in a pair-wise manner for Nt > 2. When used graphically, A and B actually are nodes in the graph that we call a fusion schema.

Three-variable schema. For Nt = 3, the pair-wise fusion situation is still graphically very simple. Consider raw data elements, A, B, and C, and fusion result, F1, for A – B fusion. F2 is the result of a fusion between F1 and C. Because we have restricted fusion to pairs only, Nt = 3 is still a very simple case.

Four-variable schemata. For Nt = 4, two fusion schemata are possible. One is the four-node analog of the three-element case that minimizes the number of raw-data pairs involved in fusion. Here we have four nodes, one for each raw data element: A, B, C, and D. F1 and F2 are defined as above and F3 is defined as the result of fusion between F2 and D. This fusion schema, which we call S1, minimizes the number of fusion events involving raw-data pairs. In fact, the structure of any fusion schema with only one raw-data pair can be specified entirely by S1 and Nt.

In contrast, the other fusion schema for Nt = 4, maximizes the number of fusion events involving raw-data pairs. In this schema, called S2, A fuses with B to form F1, whereas C fuses with D to form F2. F3 results from a fusion between F1 and F2.

Each fusion event, F1, F2, F3, etc. will have a fusion latency associated with it. We call these latencies respectively tF1, tF2, tF3, etc. We can treat these latencies as independent variables for simulation purposes.

Five-variable schemata. Three different fusion schemata are possible: S1 (only one raw data pair), and two schemata that satisfy the S2 requirement to maximize the number of raw data pairs. These S2 schemata, called S2.1 and S2.2 are depicted in figures

2 and 3. They have different connectivity. The process is illustrated in Figures 1, 2 and 3.

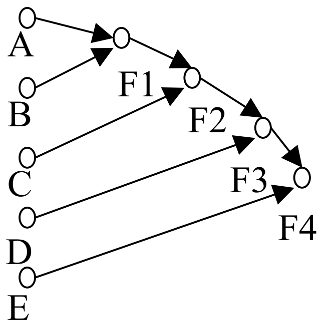

Figure 1. S1 fusion schema for five variables.

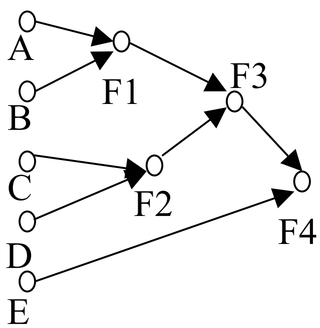

Figure 2. S2.1 fusion schema for five variables.

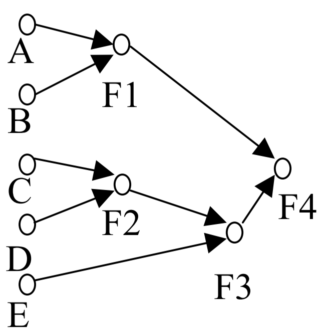

Figure 3. S2.2 fusion schema for five variables.

Encoding a schema's structure into shorthand notation is necessary to reduce the graph to machine-readable format that can be stored in a database and sent in a message. We can specify the S2.1 schema using the following notation to denote results from fusion: F1 = (A, B), F2 = (C, D), F3 = (F1, F2) and F4 = (F3, E) where A, B, C, D and E are graph nodes. The Fs are fusion results from pair-wise fusion of raw data pairs (e.g., F1), fusion between two lower-order fusion results (e.g., fig. 2, F3), or between raw data and a lower-order fusion result (e.g., fig. 2, F4). N.B. A node depends only on its parents.

To facilitate the information-compression process, we can construct more complex schemata with many nodes from simpler, smaller schemata. For example, using a shorthand notation we can say that S2.1 = S1(2) + S1(3), where S1(2) and S1(3) are the fusion schemata for Nt=2 and Nt=2, respectively. Similarly, for Nt = 4, the S2 schema is the same as S2.1 in fig. 2 except that the E node is not present when Nt=4.

6.4 Three-value logic for IFF

ROC analysis evolved for a two-value logic system whereas IFF by definition involves three alternatives. Consider the values of X = friend, Y = neutral, and Z = foe. H, M, CR and FA are determined by comparing the selected value to the correct value. K, the total number of IFF events, is the sum of H, M, CR and FA. ROC implementation requires additional details for the three-value case.

A weighting system is needed in which the weights are determined by the value of making a correct choice or the consequence of an incorrect choice. We propose the following weighting system, where the weights, w_{ij}, range from 3 in the case of a hit to a weight of –3 for a worst-case incorrect designation. The exact value of each weight is an open research question and initially is assumed not to be as important as the rank order of the weighting factors. Se is the selected value, determined from data-fusion results, and Co is the correct choice (ground truth). The rules are summarized in Table 1.

These weights are based on the following assumptions regarding the intended actions following a target-classification determination:

a. A friendly force can get help from or render assistance to another friendly force but it will not expect help from neutral entities.
b. A friendly force will either attack or be attacked by a hostile force. This assumption ignores covert operations where an attack on a hostile force may compromise the mission. Even then, a unit on a covert operation will want to make correct classifications of hostile platforms to prevent the hostile forces from detecting them.
c. A friendly force will not attack another friendly force. This assumption ignores fratricide.
d. A friendly force will neither protect, nor attack a neutral force. Neither will it expect any assistance

or resistance from it. This assumption ignores the case where friendly forces are tasked to protect neutral entities from attack by hostile forces that may have mistaken the neutral forces for friendly.

Action probably is not required if the target classification is neutral. Thus, the reward for a correct identification of a neutral force is not as high as that of a hostile force that requires immediate action.

Table 1. Proposed weighting factors for target-classification results

Correct vs. selected classification	Hostile Se = X	Neutral Se = Y	Friendly Se = Z
Hostile, Co = X	W_{XX} = 3 Hit	W_{YX} = -2 Missed target	W_{ZX} = -3 Missed target
Neutral, Co = Y	W_{XY} = -2 False alarm	W_{YY} = 2 Correct rejection	W_{ZY} = -1 False Alarm
Friendly, Co = Z	W_{XZ} = -3 False alarm	W_{YZ} = -1 Missed target	W_{ZZ} = 3 Hit

6.5 Pedigree

Pedigree is essentially the history, J, of a result. For example, J for a five-element fusion can be defined as follows: J = [a, b, c, d, e, f1, f2, f3, f4, S2.2] where "a" through "e" are the raw data elements that occupy graph nodes A through E. Values f1 through f4 are the results of fusion processes depicted in Figure 3. That is, they are the values that occupy graph nodes F1 through F4. S2.2 designates the fusion schema in fig. 3.

6.6 Dependability of the SIP

In this study, the factors that contribute to the dependability of the SIP are data availability (completeness), timeliness, and accuracy. Availability is expressed in terms of metrics like Pc. Accuracy is determined by H, M, FA, CR as described in Table 1. This can be depicted further in ROC curves when summarizing aggregated data. Metrics for timeliness include the various process latencies. These variables represent measurable quantities, each of which result in a single number for each task or a statistic for an aggregated group of tasks.

In contrast, pedigree, which is a form of metadata, is more difficult to quantify, especially in a compressed format. The pedigree of a fusion result can require much more space allocation than the result itself. In this study we initially define confidence as the completeness of the pedigree information that reaches the decision maker. Certain aspects of pedigree can be captured in a shorthand notation that specifies the input variables and depicts the fusion schema. For simplicity, we omit from this characterization of pedigree the identity and quality of each fusion algorithm. Introducing this element could be the topic of a follow-on research project.

The dependability of the SIP for a single event or task is given by dsip = f [Pc, Nr, Nt, tc, td, tf, W_{ij}, J, ∂t] where ∂t is the time period during which the task occurs. The exact form of the dsip functionality is an open research question. The overall dependability of the SIP for an extended time period, ∂T, can be expressed as a weighted average of the dependability functions, dsip, for each target identification or characterization event that occurs in the battlespace during ∂T. Initially, the weights can be derived from Table 1. However, in a more advanced stage of the study, more specific weighting factors can be assigned to denote whether a specific target is a center of gravity or some other high-value asset.

Thus, Dsip = f [$\sum$dsip/K, ∂T] where K is the total number of IFF events that occur during ∂T.

7. Simulation data-set generation

A random-number generator can be used to construct a distribution of complete pedigrees. We will include in the test data set some pedigrees that are incomplete varying the percent of complete pedigrees as an independent variable. A convenient way to construct distributions is to very this percentage by quintiles according to the level of completeness: 0%, 20%, 40%, 60%, 80% and 100% complete for statistically significant data sets of fusable data clusters.

Other independent variables also can be selected randomly. For example, we can select a distribution of latencies for data arrival defined as the time between the arrival of the second data element in a fusion cluster and the onset of the fusion process. Similarly, the other latency can be selected from a distribution to be the time from the onset of fusion to the completion of the fusion process for a single pair of input variables, to include raw data elements, (A, B, etc.) and intermediate fusion results (F1, F2, etc.).

We can select and vary the distribution of fusion times and the percent of data sets for which fusion is incomplete.

8. Models

The process of model evaluation and selection is in progress. A survey of models that pertain to battlespace scenarios has been completed. Thirty-two models have been selected for additional consideration from a total of 926 surveyed. The main challenge here will be to select or develop a model to evaluate the metrics of effectiveness and dependability.

9. Directions for future research

In a future study, fusion mechanisms can be treated as intermediate dependent variables that depend on the fusion process and its inputs. Quality-of-service metrics need to be established for data fusion algorithms and for sensor networks in general.

Technologies to support data fusion include knowledge-based systems and intelligent agents. A great deal of work has been done regarding clusters in databases [1] knowledge bases [6] and in data mining [4]. One direction of further inquiry is to determine how these techniques can be applied to clustering of data into data sets for fusion algorithms, and the automatic retrieval of data using intelligent agents for fusion tasks via intelligent agents.

Acknowledgements

The authors thank the Office of Naval Research and the SPAWARSYSCEN, San Diego, Science and Technology Initiative for their support of this work. The authors appreciate the assistance of Tedd Wright and Holly Robins of SPAWARSYSCEN, San Diego. This paper is the work of U.S. Government employees performed in the course of employment and no copyright subsists therein.

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