Bayesian-Game Modeling of C2 Decision Making in Submarine Battle-Space Situation Awareness

Jeffrey D. Hicks, Gregory Myers, Alexander Stoyen
21st Century Systems, Inc., 6825 Pine Street, Suite 101, Omaha, NE 68106
Jeff@21csi.com

Qiuming Zhu
Department of Computer Science, University of Nebraska at Omaha, Omaha, NE 68182
Zhuq@unomaha.edu

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ABSTRACT

In a previous paper of ours [HPSZ02], we addressed the C2 decision support issues and introduced software agent architecture for combat C2 tactical decision aids under overwhelming information inflow and uncertainty. The research described in this paper is further concentrated on applying a Bayesian-Game-theoretic approach to multi-source data fusion for achieving the situational awareness that supports C2 decision making in time and mission stressed settings with significant amount of information uncertainty and inaccuracy. The Consolidated Undersea Situational Awareness System (CUSAS) provides information management and integration by applying an evolutionary games theoretic model to state determinations and conflict resolutions in a mapping between the combat space data sets and the situational state estimations. A Bayesian probabilistic computation is conducted to evaluate sensory and environmental inputs and quantitatively rank the situational state hypotheses in terms of certainty functions. Asynchronous and intelligent agents are employed to support the prioritization, management, and coordination of the data fusion process, as well as to model adversarial and friendly behavior for providing advices to decision makers or other software agents playing human roles. The agents with data fusion ability are to learn and cooperate to process overwhelming combat information more accurately, systematically, and in a well-prioritized manner.

I. INTRODUCTION

While without question combat command and control is a complicated undertaking across most, if not all, military operations. It is particularly hard for those situations with significant amounts of dynamically changes, uncertainty, and at best, partially accurate critical data. One scenario that fits well to this domain is commanding and operating a nuclear attack submarine, such as a Los Angeles class boat (688 or 688I). To quote the ADPA/NSIA study on information management [ADPA/NSIA98]:

> *The SSN force of the future will be inundated with data from on board sensors and external sources. To affect optimum tactical command and control, the CO needs to turn this data into information and knowledge quickly and efficiently.*

In fact, owing to both (1) uncertain, partially inaccurate and partially unavailable information of the enemy and the environment, and (2) very capable counter threats, an SSN may at times find it very difficult to maintain informational, electronic and general combat superiority over enemy boats and other hostile assets [KKTW96]. We are very motivated by this problem quest, and would like to address it by providing a performance accounting methodology and a concomitant system software to assist the SSN team (CO, XO, OOD, sonar-men and others) in their exceptionally hard jobs of acquiring accurate situation awareness in complex combat settings.

Basic researches are needed in a number of areas to build that kind of intelligence-demanded battle space situation awareness systems [AMS96]. For example, mathematical foundations of information fusion must be first established [K85, KRTB90, OSKS97]. The kind of robust, integrated fusion architectures for handling increasing diversity of input sources are especially important in contemporary command and control (C2) missions [Dawidowiez99]. A well crafted computer system integrating knowledge acquisition tools and proper decision support models can assist military planners in their tactical decision-making in many different ways, particularly with respect to quickly identifying responses and counter-responses to enemy action or inaction [KKTW96, DeJB97]. Unit commanders would apply such a tool in order to determine the best allocation of tactical resources, to accomplish the unit's assigned mission, and to satisfy the commander's strategic intent. When the unit staff uses a suitably automated "war gaming" tool to support Course of Action (COA) analysis, the commander can quickly gain a comprehensive understanding of the action-counteraction dynamics between the opposite units, thus increasing the assurance factor of the mission success.

In a previous paper of ours presented in the 2002 International Command and Control Research and Technology Symposium (ICCRTS), Monterey CA, USA in June 2002 [HPSZ02], we addressed the C2 decision support issues and introduced a software agent architecture for combat C2 tactical decision aids under overwhelming information inflow and uncertainty. The research described in this paper is concentrated on multi-source data fusion for achieving the situational awareness that supports C2 decision-making in time and mission stressed settings with significant amount of information uncertainty and inaccuracy. We applied a Bayesian-game approach to the achievement of situation awareness through multi-source data fusion for commanding and operating a nuclear attack submarine. The Consolidated Undersea Situational Awareness System (CUSAS) provides information integration, management, and decision support under uncertainty for submarine operations. The system uses a combination of Bayesian network and Gaming Theoretical inference technology to enable COs to quickly obtain an uncluttered view of the battle space situations, so as to efficiently model operational plan, such as coordinated multi-force strike scenarios based on the integrated information acquired through the data fusion process. In cooperation with submarine officers, the software system examines various tradeoffs, including speed of maneuver versus detections and probability of collisions.

In the data fusion process a two-person, non-zero sum, non-cooperative game (TNNG) model is applied. In TNNG games it is possible to have multiple Nash Equilibriums (NE) [Ghosh98, Gintis00]. Since there are non-zero sum outcomes, the outcomes need to be represented separately in two matrices, one for each player. The situation may be complicated by the fact that the dominant NE can only be achieved through probabilistic evaluations [Qian95]. Essentially, it is a process of evaluating a series of games that may take place under somewhat different conditions of probabilities. The optimal strategies are considered under the evaluation of the Bayesian probabilities. The relationships between the evolutionary game model and the Bayesian probability model in a C2 process are designed to work in the following courses: (1) The evolutionary games theoretic (GT) model is in charge of state determinations and solutions to the mappings between the data sets and the situational state hypotheses. (2) The Bayesian probabilistic network (BN) evaluates sensory and environmental data and quantitatively ranks the information entities (packages, blocks) in terms of certainty functions. Bayesian probability enables reasoning under uncertainty and combines the advantages of an intuitive representation with a sound mathematical basis in the games. The benefits of Bayesian probability stem from the fact that it is able to accommodate both subjective probabilities and probabilities based on objective data [desJarins93, Meek95, Castro98]. Moreover, the Bayesian probability can readily handle incomplete data and avoid over-fitting of data in a fusion process. Additionally, intelligent agent software provides automated data mining and integrates all of the phases of C2 operations, and provides recommended Course of Actions to the COs [KHBM96, K97].

In the current prototype, many relevant data items are readily managed, indexed and provided in appropriately hierarchical fashion. Ship position, track, coordinate, depth and other data are interplayed with zoom and pan controls, and are provided to the user accordingly. As is the case in real life, different levels of details are provided for each event, depending on the user. For instance, the CO has the ability of seeing all of the data but will routinely (by default) only be provided with high-level views, showing all ships and other elements and so forth. On the other hand, the same elements are represented to the Sonar Technician as detailed contact and track pertinent data, with the appropriate emphasis (e.g., Broadband, Narrowband and Demon displays). The Fire Control Officer has a mixture of the two views of the same data with, yet again, different attributes. Based on operator input, previously observed patterns of behavior and entered possibilities will be annotated with ranked attributes and linked to typical cases. To provide submarine personnel with an ability to solicit and routinely benefit from intelligent software advice on decision-making in the presence of significantly uncertain, inaccurate and incomplete information, information provided by one sensor will be linked to (possibly correlated) information provided by other sensors. This is particularly useful, because in the absence of correlated information, individual sonar technicians may be conservative in reporting suspected hostile contacts. Based on the stochastic game theory, modified Bayesian inference networks, and objective function optimization, the agent-based CUSAS provides summarized information to the Submarine CO (and other key Officers) for contact identification, navigation, and collision avoidance. The results are visualized on the CO's tactical display. Learning and adjustment are being implemented primarily through weight evolution in utility formulae and correlation links. As more is learned, information will be refined, re-ranked, and re-annotated. Qualitative and quantitative triggers will be installed which will force a re-evaluation of possible correlation. For instance, should a possible contact be re-classified under a set of likely possibilities where one of the possibilities is new (was not considered possible before), this may be a substantial hint for information correlation.

In the following of this paper, section II provides an overview of the theoretic foundations of the data fusion process performed by the CUSAS. Section III describes the implementation approaches of the CUSAS for the combat C2 situation awareness through the multi-source data fusion. An operational example is illustrated in section IV. Section V contains conclusion remarks.

II. OVERVIEW OF THEORETIC FOUNDATIONS

Information overload can be equally bad and often dangerous as is in the lack of useful information. Good decision-making requires an accurate or at least a plausible "degree of certainty" situational assessment and awareness through a vigilant and timely information processing, and an effective management of stress, pressure, overload, fatigue, emotional states and other distractions. In the overwhelming information presenting situation, the dominant technique of C2 decision aids makes use of utility, cost, and objective functions that capture requirements and promises of combat system components and the overall data inflow systems. Individual data sets are transformed, correlated, and fused to form a suitable and integrated objective function, which is in turn used to build the components of situational descriptions. The objective function is consequently computed as a linear expected-value summation, with constant or constant-sum weights representing significance of each hypothetic situational status [Doyle99, Kontkanen99]. For example, in most cases the inconsistency of information about the situational states should be very quickly recognized and brought to the attention of the processing and management team, saving the time and resources. However, such approaches may fail to represent adequately the situation, for a number of reasons, including following: (1) significance values may change over time, (2) individual objectives may exhibit a dependency on each other, and (3) the integrated objective relationship may not be linear [RHMM96]. Consequently and on the basis of extensive research in tools and methodologies, people have developed both detailed hierarchies and general forms for an objective evaluation and integration of the available data sets from multiple resources.

Much of the situation awareness (SA) task aboard submarines is made very difficult by incomplete, confusing and partially correct (and partially incorrect!) information from the various resources. To model friends, foes and the environment, and to provide functional, timely and relevant advice to CO, XO, OOD, Sonar Supervisor and others, we cannot rely on precise or even statistically averaged information models. Instead, we need to make use of theories suitable for modeling information and structuring information in the presence of incomplete, partially correct data and under conditions of time and mission stress. In the following, we discuss several theoretic aspects of multi-source data fusion for situational awareness in combat C2 applications.

II.1. SA Under Uncertainty

One goal of any SA system is to keep track of and use all available information in a proper and timely manner to support objective tactical planning and decision-making. However, in most situations, particularly combat C2, uncertainty can mean several degrees of things, for instance, (1) lack of good probabilistic knowledge, (2) lack of information, and (3) lack of awareness. In each case it is possible to choose one or more strategies to help inform the judgment process. Often this is based on experience and historical knowledge, which include recognition of patterns and trends, analogical reasoning, case-based inference, and evidential deductions [Dagum93, Cooper95]. Reasoning under uncertainty requires making assumptions about the condition of nature, and the intentions and methods of an adversary [Chickering96]. One usual assumption is that all parties will behave rationally, that is seek to maximize their gain and/or minimize their losses depending on the conditions and point of view from which each party is operating. If the assumption of rational behavior is true, and one can gain the same sense of the situation that the other party has, or provide the other party with a sense of the situation, then inferences can be drawn regarding most likely behavior and viable options.

Expected Utility Theory and Game Theory are conventional approaches to the study of non-cooperative adversarial relationships and options. Other methods, which may have value, are models of explicit and tacit situational knowledge that can be engaged at several level of abstraction. These methods include bootstrapping, composite judgment models, and Multi-Attribute Utility Theory (MAUT) [Cooper95, OSKS97, Doyle99]. Each is based on a linear modeling technique and has been demonstrated to provide useful types of consistent, reliable advice to decision makers in a variety of situations. Although each method is a bit different in approach, they rely on the ability to develop a linear model that expresses the explicit and tacit knowledge as a weighted utility function that is appropriate to the situation at hand. If these modeling can be done accurately, then in cases without significant and important novelty, the data analysis system will provide consistent and useful judgments and advice.

II.2. Human Factors and SA

Literature from cognitive and behavioral sciences, and supporting evidence from neural science and physiology, make it quite clear that human performance is highly content and context dependent from both an external and internal sense. (For example, recent studies have established that the mechanisms of the eye account for only 20% of human vision. The other 80% of producing an image is pattern-matching neurology in the brain.) [KHBM96]. Individual differences and even individual variability over short, medium, or longer-term time frames of perception capability and discrepancies regarding massive data processing may need to be considered [SLHM94, SM95, SM96].

Human decision making performance is in part dependent on personality and motivation, is dependent on level of knowledge, training, and natural abilities. Good performance requires strategic thinking and planning and effective use of short and long term memory, while avoiding natural biasing tendencies (recent effects, premature closure, anchoring, etc). It is clear that intelligent technologies can provide valuable assistance at many levels to an individual information analyst or collaborative group. This is accomplished by real-time software based on proper task divisions that reduces cognitive complexity, workload and short term memory demands, freeing the analyst to think more freely and creatively about strategic, tactical, and operational situation states. In submarine operations and similar stress and pressure situations, uncertainty, high stakes, biases, and long hours can have negative effects on clarity of thought and objectivity. Computerized automatic information processing system must account for these deficiencies and provide assistance to complement for the human thinking and judgment.

Bias of perception and reasoning can appear from several sources: transient or long held beliefs for which there is little or no factual support or the facts support alternative views, or perhaps more commonly, human intuitions [SLHM94]. Even carefully developed computational procedures may also pose biases in the process of evaluating certain data objects. For example, many types of bias come about because the reliance of certain type of computational assistance, while our cognitive architecture often does not support the types of things we have needed to do without external assistance. Overall, our ability to perform probabilistic and statistical calculations and mathematical inference is poor. Heuristics that we have developed to overcome this inability often are in faulty. Studies have shown a tendency to bias our reasoning by, among others, the following means:

- Ignorance: Neglect of information about prior probabilities in favor of beliefs.
- Conjunctive Fallacy: avoiding compound probabilities in favor of deciding by similarity or representativeness.
- Gambler's Fallacy: playing hunches instead of probabilities.
- Availability heuristic: using information that is most available – come to mind easily (personal experience) rather that most objectively relevant.
- Hindsight Bias: "learning" by justifying outcomes, rather than reasoning objectively about process and causes.
- Anchoring and Adjustment: we tend to be unreasonably anchored to our present beliefs and make adjustments accordingly. Anchoring often does not allow us to take sufficient account of evidence that contradicts our beliefs.
- Attentive Bias: unjustified focus on part of the information presented, rather that comprehensive consideration of the information and alternative possibilities.
- Illusory Correlation: people tend to find in data what they think (before they look) will be there.
- Primacy Effect: the order of presentation of information can be biasing, with the first piece of information given more weight independent of any measure of greater value. It is generally easier to remember the first and last items in a list, and this can provide them with greater influence on our thinking and judgment processes than justified.
- Premature Closure: making conclusions unnecessary early, that is before considering the information available that may support the conclusion or contradict it.

In some situations, cooperation can assist with mitigating natural biasing tendencies. With more study of the particular types, circumstances, and triggers that occur in submarines operations, we believe that improved judgment and decision-making can be made through cooperation and integration of data from multiple sources and reduction of the influences of biases on these processes. Game theoretic approach is one of the solutions.

II.3. Game Theoretic SA

A difficult challenge for SA achievement is that the data fusion system must strike an appropriate balance between representing game pertinent aspects of data sets while abstracting away irrelevant detail in order to achieve the efficiencies required to appropriately sample the action-reaction game space. In other words, we can't have a computer model that is so detailed that it only models a few scenarios when thousands of scenarios may need to be sampled. Likewise, the model must be designed in sufficient detail to provide useful insight to the allocation of resources [Qian95]. This understanding becomes particularly important for identifying and prioritizing "gaps" in a unit's knowledge about enemy disposition and intent since collection assets can be concentrated on enemy indicators that "tell" or "give away" tactically significant actions. This understanding can also greatly assist in the analysis of uncertain intelligence by reducing the probability of tactically "stupid" enemy actions and increasing the probability assigned to savvy opposition moves.

There are three basic perceptions to consider in a game-theoretic setting [Gintis00]:

1. *States of Nature*: These include data, information, knowledge, and beliefs about the internal and external operational environments. Clearly, the more relevant the available knowledge and the more that beliefs correspond to objective reality, the more certain the environment.
2. *Acts:* These are the objects of choice, the courses of action that are available to the decision maker. Not all acts may be intuitive or obvious. As we have learned through analysis, preferred courses of action may be counter-intuitive. The time and ability to think clearly and creatively may lead to better, non-obvious choices.
3. *Consequences:* These concern with the possible results of an action, what are the likely results, what new difficulties or benefits may arise.

The pairing of Acts and Consequences is the basis for risk-benefit (Pay-off) analysis. Game outcomes are usually represented as a matrix of payoffs [Gintis00]. Games may be played either with a pure strategy or a mixed strategy [Ghosh98]. If the optimal strategy is singular, then this is called a pure strategy (a special case of mixed strategy). If the optimal strategy requires the use of some or all the available strategies with probabilities associated with them, this is called mixed strategy. It can be proved that for two-person, non-cooperative, non-zero-sum games (TNNG), a pure strategy may not exist [Gintis00]. In this case, optimizing one's strategic position means playing a mixed strategy with probabilities attached. This approach increases the uncertainty of the opponent. The objective for TNNG is to find the optimal mixed strategy. The result of an optimal strategy is to create a Nash Equilibrium situation, that is if player A uses an optimal mixed strategy, then given any strategy taken by the player B, player A will not be better off by making another choice. Bayesian probability comes into play naturally in the TNNG with uncertainty and completeness of information available to the players [Qian95].

II.4. Bayesian Evaluative SA

When under uncertainty and incompleteness of the information sources and counter actions, the game model needs to take account of how easy it is to switch between actions, i.e., how swiftly can the unit commander response to new information, to retract actions, and to regain control points in a non-monotonic course. The benefits of using Bayesian probabilities to model uncertainty in decision support are well known, especially since the breakthroughs in algorithms and tools to implement them [Pearl88]. Game theory is closely related to probabilities even since its early age of development. The foundation of the connection was even laid off in the classics of von Neumann and Morgenstern [von Neumann53], where it stated that if the consequence function is stochastic and known to the decision-maker, then the decision maker is assumed to behave as if he maximizes the expected value of a (utility) function that attaches a number to each consequence. If the stochastic connection between actions and consequences is not given, the decision-maker is assumed to behave as if he has in mind a (subjective) probability distribution that determines the consequence of any action.

Bayesian probability (BP) enables reasoning under uncertainty and combines the advantages of an intuitive representation with a sound mathematical basis. Bayesian probabilistic evaluation has been the choice of decision under uncertainty in many circumstances assuming achieving objective goals is the sole reason for the decisions. Research into heuristics and biases show how we attempt to overcome our limited inherent computational abilities through the assistances of Bayesian probabilities. In submarines, given the closed internal environment and the ambiguous and uncertain external environment, BP is to take on a flavor all it own, with somewhat different components, interrelationships, and dynamics operating in this unique environment. The approach is to significantly influence subjective considerations and thinking about judgments and situation awareness.

The Bayesian probabilities capture many stochastic-process factors that affect the attributes of interest along with the game theory model. It can be used to predict the effects that changes of certain attributes have on a data fusion processes. For example, consider a Submarine CO to decide how to act on a reported suspicious contact. Suppose that a particular maneuver, if taken, will provide the sonar systems with an opportunity to classify the contact decisively. Further suppose that if the maneuver is indeed taken, the contact will likely prove to be harmless with a large probability value and hostile with a small probability value. In the latter case, either the maneuver will force the enemy to turn away (with a very large probability value) or the enemy will force the own boat to run away (with a very small probability value). It is likely that the CO will conclude that the only negative of the possible outcomes is not very likely (very small probability value) and indeed chose to undertake the maneuver. Consider the exact same probabilities, with raised stakes specifically, the maneuver will indeed provide a definitive classification, with the probability values for the contact being harmless and hostile being specifically defined. Clearly the situations can be effectively recorded in a Bayesian probability representation and be efficiently evaluated.

There are several ways of determining the probabilities for the entities in the Bayesian probabilities [Hanks94]. One common approach is to use the joint probability distributions of the constituent components. One of the benefits of Bayesian probability stems from the fact that it is able to accommodate both subjective probabilities (elicited from domain experts) and probabilities based on objective data. A Bayesian reasoning process can be initialized with certain background knowledge either manually or automatically extracted from certain information sources [Haddawy99]. The attributes of relevant data objects and the relations are explored in a decision support process using Bayes' rule. The Bayesian probability can readily handle missing data and avoid over-fitting of data in a decision-making process. The processing of information with multiple uncertain resources can be effectively handled by applying the Dempster-Shafer's rule of evidence combinations [Bogler87, Barnett91].

The idea of Bayesian game is to construct, for any information-incomplete game G, some information-complete game G* that are game-theoretically equivalent to G [Harsanyi67-68]. The approach involves introducing some random events (variables), assumed to occur before the players choose their strategies. The random events will determine player's cost function and other resources; and so will completely determine the payoff function in the game. On the other hand, the random event will determine the amount of information that a player will obtain about the cost functions and other resources of the other player, and will thereby determine the actual amount of information that player will have about the other player's payoff function. Both players will be assumed to know the joint probability distribution. But, each player will know only his own cost functions and resources but will not know those of his opponent; and that he will, of course, know how much information ha himself has about the opponent but will not know exactly how much information the opponent will have about him.

Learning and adapting can be incorporated in the Bayesian game model for a number of reasons. Clearly, the main reason (and the one most directly and commonly observed by the human users) will be to maintain relevancy of advice to the humans. However, the computer system that can learn and adapt will also play the roles better, that is, to interpret, filter and correlate information (e.g., track histories) more efficiently and correctly. Learning and adjustment in Bayesian game model can be implemented primarily through weight evolution in utility formulae, correlation links and so forth. This is similar to neural net learning except that there is no detailed, largely static net and there is significant autonomy of decisions within constraints. Flexibility is key given the extent of dynamic changes, uncertainty and so forth.

Overall, the relationship between the evolutionary game model and the Bayesian probability model in the data fusion system for situation awareness is as the following. The evolutionary game model will be in charge of state determinations and solutions of the mappings between the state space and the representation hypotheses. Bayesian probability model evaluates sensory and environmental data and quantitatively ranks the action alternatives in terms of cost functions. The two models will be incorporated and compensate each other in the data fusion process for situation awareness in combat C2 environment.

III. SCHEMATICS OF SYSTEM IMPLEMENTATION

A core problem in the implementation of Bayesian Game theoretic model for situation awareness through data fusion is the systematic reaction to dynamic changes of the system. Humans and computational support resources, each in their own way, need to make quick assessments and adjustments to maintain situational awareness in dynamic environments. The basic need is to react to such changes incrementally, rather than starting for scratch each time. Here we investigate several aspects of incremental computation for data fusion and support for situation awareness and study how the techniques can be applied in those different aspects.

III.1. Hierarchical Information Integration and Presentation

It is important that the way the system presenting information (in their advisory capacity) is adaptive to the human operator's needs. In the CUSAS system, the agents are to be operational in a cooperative manner, where each agent communicates and provides service to others, including human operators. For example, the system provides to submarine CO (1) an ability to process overwhelming combat information more accurately, systematically and in a well-prioritized manner, (2) an ability to solicit and routinely benefit from intelligent software advice on decision-making in the presence of significantly uncertain, inaccurate and incomplete information, (3) an ability to systematically filter, correlate, and analyze large amount of data inflow, and perform state prediction and other tasks of managing historical and current combat information, and (4) an ability to hierarchically project relevant information and systematically measure (heuristically) the quality of past and present decisions, and to project the like measures of the quality of future decisions. Specifically the software modules present information and advice to submarine CO necessary supports in time and mission critical situations such as where he wishes to avoid both collision and detection (which are sometimes conflicting objectives) in a combat C2 operation.

The design and implementation of a number of data analysis, extraction, distilling, and integration functions over the current state of affairs in submarine information management is critical to the CUSAS system. Based on operator input, previously observed patterns of behavior and entered possibilities, the information fusion agents of the system should compensate for data ambiguity, uncertainty and imprecision as follows.

1. Information needs to be annotated with ranked expectation attributes (e.g., 90% standard probabilistic expectation of the signal corresponding to a distant trawler; 7%: noise from harmless biologics; 3%: a hostile SSBN sneaking out of a haven).
2. Information needs to be linked to typical, previously observed cases of similar suspected, verified-positive, verified-negative and unknown contacts.
3. Information provided by one sensor needs to be associated with (possibly correlated) information provided by other sensors. This is particularly useful, because in the absence of correlated information, individual sonar technicians may be conservative in reporting suspected hostile contacts.
4. As more about the situation is learned, information needs to be refined, re-ranked, and re-annotated. Qualitative and quantitative triggers needs to be installed that force a re-evaluation of possible correlation. For instance, should a possible contact be re-classified under a set of likely possibilities where one of the possibilities is new (was not considered possible before), this may be a substantial hint for correlation.

We provide “texture-style” hierarchies to support representation of the combat C2 related information at different levels of abstraction. For instance, a Sonar Technician requires considerable acoustic details on the suspected and monitored contacts for which the Technician is responsible. The sonar watch supervisor requires information in less detail (but with the ability to go into more detail) about individual contacts, but needs to know about all current (suspected) contacts, as well as how the contacts on different consoles may be correlated (see below). The OOD needs to know about contacts that either need to be understood better (this may require adjustments to boat maneuvering) or for which TMA and fire solutions should be developed. The CO is likely not to require any acoustic details but needs to know range and bearing of positively identified contacts and contacts suspected or known to be hostile or presenting danger to 688’s mission. Every human in the loop will be presented with the information that is both required and in the form that is appropriate to the human.

In the current prototype of CUSAS, many relevant data items are readily managed, indexed and provided in the appropriately hierarchical fashion. Ship positioning, tracking, co-ordinate, depth and other such data are interplayed with zoom and pan controls, and are provided to the user accordingly. As is the case in real life, different levels of details are provided for each event, depending on the user. For instance, the CO has the ability of seeing all of the data but will routinely (by default) only be provided with high-level views, showing all ships and other elements and so forth. On the other hand, the same elements are represented to the Sonar Technician as detailed contact and track pertinent data, with the appropriate emphasis (e.g., Broadband, Narrowband and Demon displays and so forth). The Fire Control Officer has a mixture of the two views of the same data, with yet again, different attributes. Figures 1 shows two different displays by the CUSAS for views in different types and abstractions of the information hierarchy.

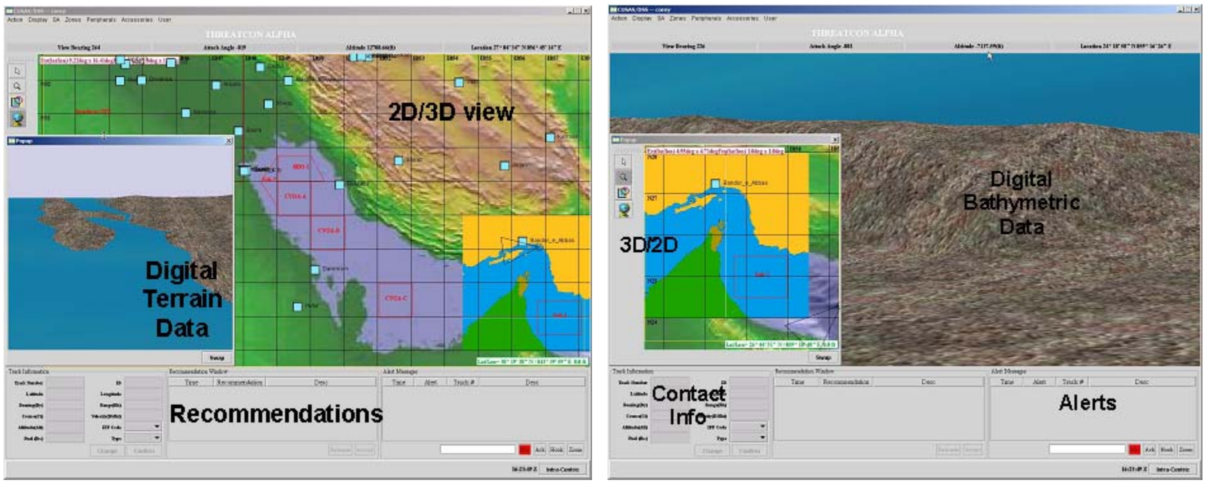

Figure 1. A schematic view of CUSAS environment and information display hierarchy

III.2. Intelligent Advices in the Presence of Uncertainty

Recall that an objective of this work is to provide submarine personnel with an ability to solicit and routinely benefit from intelligent software advice on situation awareness in the presence of significantly uncertain, inaccurate and incomplete information. A number of functions aboard a submarine involve significant amounts of reporting up the chain of command. Typical among these is the sonar watch team. Naturally, given the very high number of possible contacts a sonar technician observes during his six-hour shift and the very low number of significant contacts that these observations will actually represent, technicians tend to be conservative in reporting possible hostile (and other relevant) contacts. We have already discussed how our software will help the technicians in managing the information as well as correlating it with the information observed by others. However, even with better management and correlation, the fact remains that the available information will still be imprecise and uncertain. Thus reporting will still be partially based on exact knowledge and partially based on subjective judgment.

Our agents will provide reporting personnel, such as sonar technicians, with judgment strengthening in cases where the software also believes that the report about to be made is likely to be correct. Armed with the support of the agent, the human will feel more confidently about the reporting. Similarly, where the software believes the report to be incorrect, the agent will play Devil's Advocate and ask "what if" questions. It is possible that the human will change his mind. Otherwise, the human may still stick to his decision. In the latter case, it is possible that the agent will learn from the human and adjust its own reasoning. One key area where we are addressing partial information-based reporting is, naturally, in contact detection and tracking. For example, in our prototype an agent assisting in contact detection reports on a possible contact within a probability of certainty (e.g., *Target course: 322 degrees,. reliability 60%*). Work is under way to extend to include multivariate certainties, as well as certainty correlation.

Another issue about implementation of intelligent advices is the application of an expected utility of decisions. Expected utility of decisions modifies and, sometimes, even reverses classic deductive reasoning which is based on the standard probability theory. Consider the same sonar technician as in the previous example observing the very same possible contact, except at the beginning of the shift. Probably, given the low probability of significance, the technician will not even report it. Suppose now that the same possible contact is observed after a similar contact some time in the past turned out to be significant. Now, the technician will most likely report it. Yet suppose that the same possible contact appears after multiple similar contacts turned out to be insignificant, the technician will likely discard this contact as well. Imagine that a contact is likely to be a school of fish with the probability of 90%, a hostile submarine with the probability of 5% and a neutral tanker with the probability of 5%, according to one particular sonar system, manner by technician A. In the absence of other information, A is probably not going to raise an alarm and assume that until something changes significantly in the contact, the contact is harmless. Suppose that technician B, manning a different sonar, observes a contact, which is likely to be a neutral tanker with the probability of 90% or a hostile submarine with the probability of 8%, and a school of fish with the probability of 2%. In isolation, B too is likely to assume that the contact is harmless unless something changes very significantly. So, depending on other factors (observations, fatigue, etc.) that do not by themselves alter likelihood or probability of the contact being significant, the same possible contact is treated differently by the same technician.

Clearly, basic probability axioms, including independence of observations, fall apart here (This is similar to gamblers thinking that they are on a roll or having a bad streak.). The reason the technician behaves in this manner is that expected utility (i.e., loss or gain) of his decision whether to report the contact as significant depends on more than just the raw probabilities. In particular, the technician (possibly rightly) lets previously observed patterns influence his decision, because he expects the current observation not to be independent of the previous ones any more. Similarly, the technician (likely wrongly) lets his fatigue (and frustration, inability to properly pay attention after a long shift) influence his decisions as well, because something has to occur differently eventually. The latter situation, incidentally, can also be interpreted as classic counter-inductive reasoning. That is, it is precisely because X has observed a pattern occurring, that X expects the next observation to break the pattern.

So far in our software prototype, information is presented in a prioritized manner. For example, color-coding is used to indicate type of threat (e.g., red for collision, yellow for detection). Spatial, intuitive representation of information is used to delineate options (e.g., three rings: middle representing present speed, inner representing decreased speed, outer representing increased speed). Minimal and to the point (and time-separated as per the CO's risk aversion and the time-criticality of the stress) reporting and advice display is provided. Overall, with the present prototype, a CO (or XO or OOD) can decide fairly quickly and naturally on the best course of action, to avoid a collision and/or detection. Pattern recognition and later anticipation of human decisions will be used extensively. If a human does decide as anticipated, the particular "pattern" will be remembered and re-enforced. On the other hand, an unanticipated decision may result in a re-work of the current utility weights and correlations. At present, there is only one instance of learning in the prototype. Specifically, contact and track reporting software learns what a contact is over time. Initially, only the basic fact that something is out there, in the direction of a relative bearing X, is known. Over a period of 60 seconds within a detectable envelope of operation, the software progressively learns more about the contact. After 60 seconds, the knowledge is sufficient to classify the contact accurately. As we go forward with this work, learning, measuring and adaptation will be much more widespread.

III.3 Augmentation of Human-Machine Operations with Intelligent Agent Support

Yet another objective of our research is to conveniently and naturally augment human-machine combat operations with intelligent agent support. We have already discussed the nature of intelligent agent support in this text. The recommendation mechanism is intended to help COs avoid these events. The basic idea is to merge information from multiple sources within the vessel, and after assessing the situation to make a recommendation in a manner that can be interpreted and acted upon in a minimal amount of time. The assumption is that in near-collision cases, reaction time is critical, and therefore the system has to display the information in a way that can be "digested" instantly, and the operational options can be acted upon very quickly.

The system architecture of CUSAS provides the following human-machine interaction components supported by intelligent agent technology. Every human decision maker and information provider on a submarine is associated with the agent assistance to help the human reduce the problem space under consideration, prioritize and process efficiently relevant informational elements, and consider alternative decisions in an informed manner. The agents also provide intelligent qualification and quantification of uncertain information, utilities of particular decisions, risk aversion, and so on. Very significantly, agent decision-making support may be vital where tradeoffs need to be considered, to address conflicting objectives. Even in our, admittedly simplified and straightforward, current prototype, we have seen tradeoffs between collision avoidance and detection avoidance (e.g., a fast run may avoid the former while essentially guaranteeing the latter). Some of these tradeoffs occur seemingly suddenly, with precious little time to react. Worse yet, correct reactions may be not so obvious (in some cases for instance, a reasonable course reaction may well include a speed increase). We expect very complicated and uncertainty-ridden tradeoffs to emerge as we continue with this work. Agent support will be essential to the human decision maker in the presence of such tradeoffs.

Additional agents are provided to coordinate, synchronize and arbitrate assistant agent and human operations, to play human surrogate roles, and to support mundane but computationally intensive and tedious tasks, e.g., evaluation of tracks in the presence of history of similar tracks, reporting, and so on. Communication exchanges are provided to facilitate human-machine interaction, in a uniform manner among humans, agents, and sensors that in turn provide communication with the outside environment.

The overall purpose of our software is to help driving the ship in a tactically safe manner. Clearly, the agents will need to work with the humans in a carefully thought through and trained manner. Given the conditions of stress and overwhelming information overload on a modern submarine, if the software is not perceived useful, it will be ignored or turned off. It is also very important to understand that we have no ambition to provide a combat "auto-pilot" or to otherwise fully automate the undersea combatant. Rather, we provide systematic intelligent assistance, based on a rigorous and useful theory, to humans. The assistance will be primarily for commanding and reporting tactical decision making alternatives regarding maneuver, contact, and collision avoidance.

IV. EXEMPLAR ILLUSTRATION

In this section, we give an exemplar illustration of the data fusion activities of the CUSAS for situation awareness in time and mission critical operation. The illustration uses collision/detection as an example.

We first describe some of the logics behind the collision/detection mechanism. We make the following assumptions:

- The event horizon is 30 minutes. Most likely, it is not a safe to assume that any vessel will continue in the same course and speed for longer than that time slice.
- As hinted above, we assume constant speed and course of all vessels (once a course is selected)
- It is also assumed that speed/course changes are effective immediately. This means that the difference between the current course/speed and any other does not effect the calculations. Note that since in reality the turn rate depends on the amount of rudder applied, it is next to impossible to make any realistic predictions without ignoring this factor.
- Last, we ignore the effect of the relative approach course on the effective size of the vessel as a factor in the collision. We assume a uniform size (the length) in all directions.

The simplest case of collision prediction is calculating whether for a given current location and speed of both vessels, and the bearing of the other vessel, there is a course that if taken will lead to collision. There can be four cases: (1) No collision, (2) One collision point, (3) Two collision points, and (4) Imminent collision. The four cases are illustrated respectively below.

(1) *No Collision*. If the bearing of the other vessel is such that it is going away from out current location, and our speed is slower that its speed, there is no course we can take that will lead to collision. Even if the vessel is heading towards us, but its there is no intersection point of the two courses where both vessels will be at the same time, a collision is not possible. For example if we are moving slower than the other vessel, and the closes point it will be to our (current) location is far enough so that even if we "aim" directly at that point, we cannot make it to that location before the other vessel travels past it.

(2) *One Collision Point*. This is the "classic" case. For given starting points and speeds, there is only one bearing we can follow that will lead to the *timed* intersection of the travel lines, i.e. collision. Note that under the above time limited assumptions – if we follow the lines indefinitely, there will be, of course, infinite number of collisions possible.

(3) *Two Collision Points*. Even under our assumptions, if the other vessel is far enough and its travel direction is towards our location, it is possible to have two collision points. This can happen when the contact speed is greater then that of the controlled vessel one, and the contact is moving towards the controlled vessel.

(4) *Imminent Collision*. This may occur when the vessels are close enough. The CO may not have enough time to change the controlled vessel speed or bearing. It does not matter anymore which way the ship may try to go – a collision will happen.

All of the above hold for detection, except that since detection happens within a (somewhat distorted) sphere, the result is not a point, but rather a range of courses that will lead to detection. In addition, effective detection distance depends on the speed of the other vessel as well as on our speed, and the relative course between the vessels. Even more than in the collision case, it is possible that at a close distance, detection will happen no matter which course is taken. The foundation of the detection algorithm is based on the following rules:

- Detection range will linearly *increase* as the speed of the target increases. At speed zero, there will not be any detection.
- Detection range will linearly *decrease* with the increase to the detector's (vessel) speed
- Detection range is the same in all directions, with the exception of targets that are in the wake of the detection vessel. In-wake detection range is reduced by a constant factor. (this is not effecting the recommendation generation at this point, just the SSA display.)

The representation of collision/detection risk is done as three (partial) circles centered around the own ship. Each sequence of arcs represent the risks at a given speed, where the middle circle represents the current speed, the inner circle represents the current speed minus 5Knts and the outer circle -- current speed plus 5Knts. Exceptions to this rule are the cases where either the plus or the minus 5Knts speeds are outside operational envelope of the vessel, in which case that circle will not be drawn (and the result will be only 2 circles). Each circle can consist of the set of arcs, where the arcs may be of one of two colors: - Yellow or Red. Any course that is outside the yellow or red area is safe. That is – own ship will not collide with, or be detected by other vessels. A course that "intersects" a red segment has a very high probability of ending in a collision. The yellow zone represents courses that while not leading to collision will lead to probable detection by the other vessel(s). Note that within the arc, there is an even distribution of the chance for collision/detection.

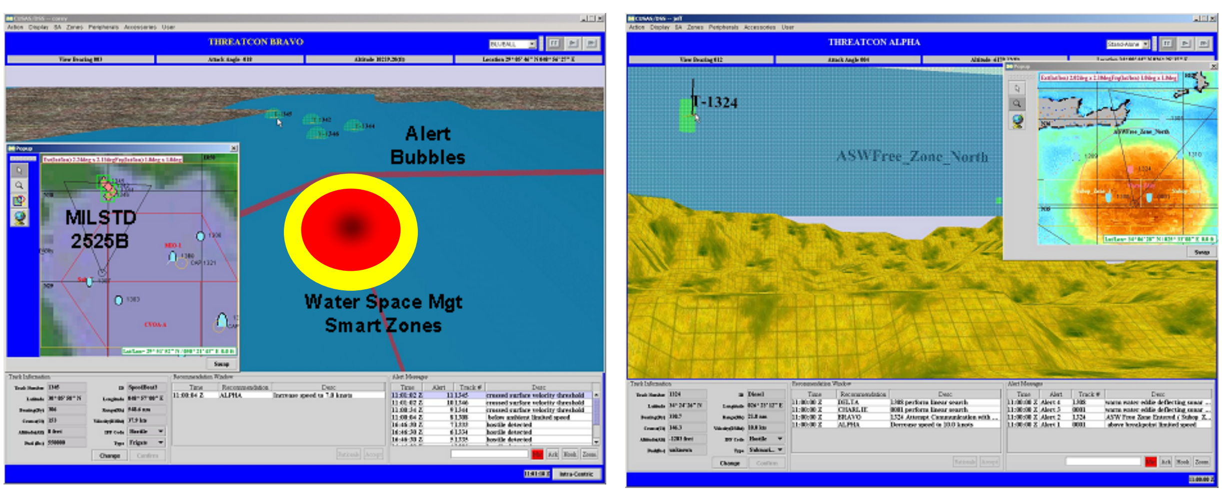

Figure 2. Situational Awareness display through multi-source data integration

While the above discussion assumes that we know all of the parameters of the battlefield, this is not the case in real life. In particular, when an object is first detected, we know very little about it. In the current prototype, we assume that the learning process is linear – so that after every second since the initial detection the information available to us is more detailed, as well as more reliable. After a full minute of continuous tracking and analyzing, we have all of the information, and therefore we can use the above algorithms to predict collision/detection. However, until that point in time, we have to add to all of our calculation a "fuzziness" factor: we have to assume that the information has only some percent reliability, and that it will get better in time. Therefore, during the first minute after initial detection, the recommendation analysis does not assume a precise location and/or speed of the other vessel. Instead it assumes a range that is bound by the known limitations (such as speed can't be more than X Knots). The algorithm will converge on the "correct" data as time progresses. It is also true that if we loose a contact, all data known is also lost, and if the same contact is reacquired, the learning process will repeat as if it is the first time it is detected. All of these will, in time, converge to the "real" solution. The solution will then produce vessel identification and (as described above) a maximum of two collision points, and four detection arcs. Again, please note that in the early detection interval, when the reliability factor is low, we "err" on the side of caution, and therefore the messages will assume the worst case scenario, and time estimates listed are the earliest the condition can occur. As an illustration, observe the two progressive agent observations (with data reliability progressing from 16% to 66%). Once a contact has been identified and properly designated, reliability is 100%.

V. CONCLUSION

The problem space of the battlefield is very complex, subject to continuous changes, and presently cannot be well modeled due to the associated combinatorial complexity. To be effective the MAS must be able to quickly reorganize its computational assets to meet the dynamic changes of the environment as well as to deal with incomplete sets of information. The multitude of variable elements and their relationships, which define the problem space, create a computational and combinatorial complexity. The constantly changing strategic, tactical, economical, political, and sociological conditions make the modeling conceptually elusive and computationally highly demanding. However, the significance of MAS in Command and Control (C2) applications is yet to be fully demonstrated.

The complexity and efficiency of a multi-agent system depends on the number of software agents employed, and the degree of interdependence between them. While the power of multi-agent systems is inherited in the individual agent entities, it is amplified by the agent entities' ability to solve problems in a distributive and collaborative fashion. The larger the number of agents and the more interdependent they are, the higher the complexity and the lower the efficiency. In any cases, a supervisory control mechanism is implemented to insure the agent operation effectiveness when modeling large complex problem spaces. In CUSAS, the cognitive aspects of the agents, which is critic to the overall capabilities of CUSAS, are greatly improved by implementing techniques that stress machine conceptualization of the problem space and algorithms to allow the machine to solve problems based on integration of information from multiple resources, and achieve a better situational awareness for the submarine COs and other

C2 officers. Clearly, we have seen the need for better display, coordination and, in general, management of and assistance with information. We have made good progress on both problem domain learning, applied theory development, and submarine domain-relevant software design and prototyping for the objectives.

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