Intelligent Agent-Based Software Architecture for Tactical Decision Aid under Overwhelming Information Inflow and Uncertainty

C2 Decision Making & Cognitive Analysis Track

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Abstract

In the highly dynamic and information rich environment of military submarine operations, the Commanding Officer must make split second decisions that could ultimately result in the destruction or survival of ownship or the accomplishment of its designated mission. Despite extensive training and expertise, the fog of war often shadows real world encounters. Pieces of the tactical puzzle may be scattered, broken, and/or even missing. It is the Commanding Officer's job to meld the fog into a clear tactical picture and intuitively decide upon the optimal course of action to obtain his mission goals and objectives. A mathematically derived optimal solution could be used as a decision making aid for the Commanding Officer to enhance ownship's performance. A highly innovative hybrid Bayesian/differential game modeling approach is being developed utilizing 21CSI's Agent Enhanced Decision Guide Environment (AEDGE™), a COTS based agent architecture, to tackle this problem. The resulting decision aid will facilitate submarine operations by addressing such practical problems as tradeoff evaluation for course of action and maintaining tactical advantage while avoiding counter detection.

1 Introduction

The task of providing accurate, timely, and focused decisions in submarine tactical command and control environment is a complicated problem. Difficulties arise from the inherent uncertainties embedded in the situations, such as the imprecision of the sensory data, the unpredictability of the *Contact*'s tactical picture, and the inadequacy of the decision model and reasoning methodology.

Action determination is performed in a complex decision space consisting of a large parameter set that includes the evaluation criteria, constraints, and action alternatives. In most situations, neither the sets of available information are complete, precise, and consistent, nor would the decision space and its parameter set be defined unambiguously.

In the highly dynamic and information rich environment of military submarine operations, the Commanding Officer (CO) must make split second decisions that could ultimately result in the destruction or survival of *Ownship* or the accomplishment of its designated mission. Despite extensive training and expertise, the fog of war often shadows real world encounters. Pieces of the tactical puzzle may be scattered, broken, and/or even missing. It is the CO's job to meld the fog into a clear tactical picture and intuitively decide upon the optimal course of action to obtain his mission goals and objectives. The problem always comes under the assumption that the CO and his staff have certain amount of information about the contact and limited knowledge for modeling the action/reaction of the contact. But the information never comes to be complete and/or hundred percent accurate. When under uncertainty, the system needs to take account of how to switch between actions and response to new information, to retract actions, and to regain control points. How do they properly make maximum use of the information and how do they make decisions based on the most effective use of the information? It is desirable to have a computer system automatically process the collected information, evaluate the alternatives and provide on-time assistance to the CO for making the decisions.

A great deal of work has been devoted to the study of the nature and formalism of various decision models and quantitative reasoning techniques such as the differential game theory, Bayesian statistics, and utility economics, to taper off the uncertainty problems in decision making. However, most studies have concentrated on individual models and techniques. Little has been done to unify them coherently to provide a collective solution. This paper explores the problem from the perspective of two fundamental theories and their complementary roles in decision science: differential game theory and classic Bayesian probability theory.

A mathematically derived optimal solution could be used as a decision making aid for the CO to enhance ownship's performance. Specifically, it is known that

- The use of computer technology affords a rapid and efficient manipulation and exploration of enormous amounts of available information to deliver real time optimal strategies in a dynamic environment.
- The enormous storage capabilities available in today's computer systems allow processing of historical data and prior experience as no human can.
- The advances in game theory, artificial intelligence and software agent technology allows for drawing optimal solutions available to the CO in real time.
- Using sufficient knowledge and feasibility estimations in heuristic reasoning, the decision aid can determine up-front whether certain objectives can be fulfilled.

A COTS based agent architecture, 21CSI's Agent Enhanced Decision Guide Environment (AEDGE™), will be utilized to implement the decision aid methodology. The computer decision support system will determine the optimal strategy and a set of actions for unit commander to choose after receiving and collecting necessary information from various resources (from both own side and the adversaries). The knowledge acquisition and decision support tool will provide advice and a coherent plan of actions to the Commanding Officer (CO) under the concerns of the following uncertainties: (1) measurement uncertainty which comes from sensor noises, environment dynamics and complexity in terms of the presence of different parties in the area, the limitations of sensor detecting ranges, etc.; and (2) unpredictability of the contact's actions - the contact may unaware of the presence of own unit. In case it knows us, it may be able to estimate and predict our moves, and take the best counter action toward us, while the own unit makes estimation and predictions of the contact's move and actions.

In the following, we will first present an overview of game theory based decision aid systems and techniques that address the problems of tactical decision aid under overwhelming information inflow and uncertainty in section II. The principles and computational details of the differential games and Bayesian statistics for tactic command and control environment are then described in section III. The theoretical discussions are assisted with example illustrations. The AEDGE™ architecture and its application in implementing the decision aid model are described in section IV. We use diagrams and examples to illustrate the coherent relations among the software modules and the functionalities each of the modules will play in terms of their implementation of the mixed strategy. The section V briefly summarizes the major technique points of the paper.

2 Game theoretic decision aid

A well-crafted computer software system can assist military planners in their tactical decision-making, particularly with respect to quickly identifying responses and counter-responses to enemy action or inaction. Unit commanders would apply such a tool in order to determine the best allocation of tactical resources to accomplish the unit mission and satisfy the commander's intent. When the staff uses a suitably automated "war gaming" tool to support Course of Action (COA) analysis, the unit commander can quickly gain a comprehensive understanding of the action-counteraction dynamic between the opposing units.

The term "Differential Games" is applied to a group of problems in applied mathematics that share certain characteristics related to the modeling of conflict [Isaacs 1965]. In a basic differential game's setting there are two actors - a pursuer and an evader - with conflicting goals. The pursuer wishes, in some sense, to catch the evader, while the evader's mission is to prevent this capture. These "games" are modeled mathematically by first defining state variables that represent the position (and perhaps velocity) of the participants, determining (differential) equations of motion for the rivals, and then describing sets in the state space called target sets. (For example, a target set for a pursuer may include points in the state space where the distance between the pursuer and the evader is small.) Each participant in the game tries to drive the state variables of the game into a particular target set by controlling key variables called, naturally, controls. The study of these games has implications for real-life air combat.

Pursuit-evasion games have been applied in modeling predator chasing prey, a missile chasing an aircraft, or the like [Hajek 1975, Petrosjan 1993]. Unlike most other games, the players may have to make continuous decisions, for example deciding on a real-valued turn angle at every moment in time. Thus, it has a feature of dynamical games. An archetypal example of a differential game is known as the Homicidal Chauffeur [Isaacs 1965]. In this game, the driver of a circular car acts to knock down a pedestrian, who, of course, does not wish to be flattened. The car can move faster than the pedestrian, but the pedestrian can maneuver better. What is the best strategy for the pursuer (the car) and the evader (the pedestrian) to follow in order for each to achieve their conflicting goals? The situation of submarine in a battle space is the same as this game model. The solution to this problem can be applied to air combat where a slow, but more maneuverable airplane is pursued by a faster but less maneuverable craft.

We will limit our discussion to a two-player game problem in this presentation. It is straightforward to extend it to multi-player problems. In fact, in most research and practical study, the multi-player game problem is often treated simply as multiple two-player game problems. To better understand the principles and methods behind the system structures of the military tactic decision making system, we'd like to first recognize some specific features described in terms of differential games paradigm. The features include the following:

(1) Dynamic game – The process involves actions and counter-actions from adversary players. That is, it is generally a multi-player, multi-objectives, multi-variables, and adversary game problem.
(2) Continuous action game - That is, the players involved in the game are committed to adopting and adjusting actions all the time. Also, the game actions are nomonotonic - players are allowed to alter actions any time upon receiving new information.
(3) Evolutionary game - There will be game state changes continuously and be infinite number of possible states in long run.
(4) Simultaneous game – the players may have or have no knowledge about the identity and actions of each other while making their own decisions. That is, one player may make a decision based on the information and the (estimated) action made by the other player at the same time or after the other player takes an action.
(5) Non-deterministic game – Generally, information available to the players are uncertain (especially the opponent's plan, action, reaction, etc.), incomplete, and dynamic. However, the certainty of information improves when stayed longer and have done more measurements. For example, the velocity of contact and the prediction of the trajectory are uncertain on the first few attempts of measurement and prediction; but the certainty increases (uncertainty decreases) when more and more measurements and predictions are made.
(6) Informed game – There exists information exchange, detection, and prediction between players. In general a player makes decision based on the combined information of (a) environment and sensor data, (b) acquired facts of the other player's previous action, and (c) estimated facts and prediction of other player's current action.
(7) Game with incomplete information: The players are uncertain about some important parameters of the game situation, such as the payoff functions of the opponent or even the player themself, the physical facilities and strategies available to other players or even to themselves, the information other players have about the various aspect of the game situation, etc.
(8) Bayesian Games: each play has a subjective probability distribution over the alternative possibilities. 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 [Harsanyi 1967-1968].

The analysis of these features helped us to figure out a decision-aid model and design strategy that address the tactic decision aid problems possessing these features. Such decision aid system in tactic decision aid is based on the theory and models of dynamic continuous-time infinite dynamic games. The multi-variable, multi-objective optimization model is rooted (started) from the development of optimization theory during the World War II. As indicated by Basar [Basar 1982], the term "differential game" became a general name for games where differential equations play an important role. The term is also being used for other classes of games constituting a class of decision problems where the evolution of the states is described by a differential equation or some other forms of dynamic system representation and the players act through a time interval.

The differential game theory models the submarine tactic decision making situations by a set of differential equations that describe the objectives and constraints that are solvable by the traditional optimization methods [Ghosh 1998]. The elegancy of the differential game theory lies on the Saddle-point equilibrium principle (the principle of minimax game theory) [Gintis 2000]. The principle states that the fundamental of game theory is (for a player A) to choose the move (action) such that its maximum loss (loss ceiling) is no bigger than that (the maximum loss) of the other alternatives under the assumption (condition) that the other player is to adopt the best counter-action against player A's move. Or, in other way of saying this, choose the move that the minimum gain (gain-floor) is no smaller than that (the minimum gain) of any other alternatives (no matter how large the maximum gain would be with the other alternatives) under the condition that the other player is to adopt the best counteraction against player A. Specifically, the differential game model for the submarine tactic decision aid consists of the following components.

(1) two players (ownship and the contact) that form the two sides of the game in the game, denoted as P_1 and P_2.
(2) a time interval [0, T] within which continuous decisions (game playing) are to be made.
(3) an infinite set of states s = {x(t)}, where $t \in [0, T]$, denotes the environment. A sequence of states $s^0, s^1, \ldots, s^q$ is a state trajectory that depicts possible consequences when an action (decision) is made.
(4) a state value (evaluation) function for each player, denoted as $\eta_1(s^i)$, and $\eta_2(s^i)$.
(5) a definite set of action (control) alternatives for each player, denoted as $u_1^i = \{u_1^i(t)\}$ and $u_2^i = \{u_2^i(t)\}$; i = 1, 2, …, c.
(6) a cost function for each player: $L_1, L_2 = g(t, x(t), u_2^1(t), u_2^2(t), \ldots, u_2^c(t))$.
(7) a differential equation $\frac{dx(t)}{dt} = f(t, x(t), u_2^1(t), u_2^2(t), \ldots, u_2^c(t))$ describes the state changes (evolution) of the game.
(8) a mapping $u^i(t) = r^i(t, x(t))$ is a selection of a permissible strategy (action alternatives).
(9) information structure – a set of information fields that are accessible by p1 and/or p2.

The principle in tactic decision aid is to maximize the ownship's prioritized objective function with minimum cost by taking considerations of any counter-actions the other party may take. The decision making model prefers the setting of the cost function properly so that it leads to a stable Nash solutions. The principle can be illustrated by an example below.

Let us use a chase and detection example to illustrate the processes involved in the differential game. Consider a situation in the Initial Detection/Collision Avoidance State, where the ownship is to chase a hostile while avoiding being detected by the contact. For the two players (ownship and the contact) involved, we use P_1 to denote the ownship and P_2 for the contact. The time interval parameter T is defined as to when the mission of P_1 is called off. The state set consists of vectors $x(t) = [d(t), \omega_1, v_1, \omega_2, v_2, b_1, b_2]$, that describe the distance d(t) between P_1 and P_2, the maximum angular velocity ω_i and the constant forward speed v_i (i = 1, 2) of P_1 and P_2, and the status (b_1, b_2) of P_1 and P_2 being detected by each other, respectively. The state evaluation function for player P_1, i.e., $\eta_1(s^i)$, is defined as a procedure responsible for calculating the values of d(t), ω_2 and v_2 from sensory data and deriving the b_1 and b_2 values. The set of action (control) alternatives for each player is the rudder angle $u_1^i(t)$ and $u_2^i(t)$; i = 1, 2, …, c. The cost function can be described in terms of the distance between P_1 and P_2, as a function of collision-free and detectibility. In a simplified case considering only a two dimensional space, it is $L_1 = r = \sqrt{(x_1^2 + x_2^2)}$ and $r \leq = r_m$, where r_m is the minimum distance between P_1 and P_2 that will keep the P_1 in tackle with P_2 while not being detected or colliding with P_2.

The differential equations describe the kinematics of the ownship are given as the following:

$$\dot{x}_1 = - \omega_1 u^1 x_2 + v_2 \sin\theta,$$
$$\dot{x}_2 = - v_1 + \omega_1 u^1 x_2 + v_2 \cos\theta,$$
$$\dot{\theta} = \omega_2 u^2 - \omega_1 u^1.$$

The differential equations describing the kinematics of the contact are identical to that of ownship, that is, each player is characterized by two parameters: the maximum angular velocity ω_i and the constant forward speed v_i. The control of P_i is u^i, which is the rudder angle, and is bounded by $|u^i(t)| \leq 1$. A number of state trajectory diagrams can be constructed for different sets of parameter values (different speed ratios and different maneuvering capabilities) to gain certain insights into chasing and detection sensitivity with respect to these parameters. The target set of the solution can then by described by a cylinder space $x_1^2 + x_2^2 = r_m^2$, (recall r_m is the minimum distance between P_1 and P_2 that will keep the P_1 in tackle with P_2 while not being detected or colliding with P_2). A mapping $u^i(t) = r^i(t, x(t))$ takes place where a specific rudder angle is selected as a permissible strategy of the equations under the given state x(t) with respect to the available information structure of p_1. This simple model may not be (too) unreasonable if only short duration maneuvers are considered, during which the players cannot change their speed markedly.

Though being attractive by its traditional and mathematical elegancy, the differential game theory has certain limitations in real world applications. Basically, the complexity of real world situations (which include both the nature and human factors) precludes the establishment of a sufficiently accurate, reasonably sized, and moderate level of complex equations in terms of computation time and space requirements. Many times, an analytical form of the equation used in a practical application is over simplified. To be realistic, it will be getting very complex, and very hard or almost impractical to obtain. That is, the equations may not be adequately manageable. The unrealistic over-simplification of the differential equation makes the decision based on this model come with large deviation off the target. Moreover, the implementation of the differential games theory relies on the satisfaction of the conditions that there exist unique solutions to the differential equations that formulate the state transitions of the game process accurately. These conditions may not be met in practical situations.

Many techniques have been suggested and studied to address and/or compensate the limitations of the basic differential game model. In this paper, we describe an approach that is to

(1) use a computational data structure, such as Bayesian probability representation for description of probabilistic relations of the decision states, rather than an explicit and analytic form of the differential equations.
(2) focus the state and cost evaluations on use of heuristic methods. It is to pick the action alternative that is most likely (reliably) to achieve an objective with high priority.
(3) to have multiple decision models run simultaneously and compete cooperatively to selecting a solution.
(4) to apply idea of dynamical switching among different decision models according to information gathered, as well as estimations and predictions made in terms of the stochastic models of the game.

3 Hybrid model of decision aid

It is known that the traditional deterministic model of reasoning for decision making bases on rigorous mathematical logic and indubitable data analysis has very limited ability to operate effectively in those circumstances such as the military tactic command and control operations that feature extensive underlying uncertainties. To have a reliable and clear mind setting in the absence of clairvoyance, a computerized decision aids system needs to acknowledge, represent and incorporate measures of uncertainty, quantitatively and qualitatively, and to employ human-like, stochastic and non-monotonic inferences [Doyle 1999].

Uncertainties in decision aids come from several aspects. Specifically, they include: (a) Action alternatives are not crisply distinguishable (often a broad outline), (b) Evaluation criteria are vaguely defined, (c) Constraints are ambiguous or contradictory, (d) Evidence is incomplete, imprecise and inconsistent, (e) Fitness of the reasoning mechanism to the underlying nature of the problem is unknown, and (f) Variation of the system identifications is constant due to time and situation changes. A difficult challenge for the decision support system development is that the system designer must strike an appropriate balance between representing pertinent game aspects 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 can only game a few scenarios when thousands of scenarios may need to be sampled. Likewise, the game must be designed in sufficient detail to provide useful insight to the allocation of resources. In order to strike this balance between detail and abstraction the game designer must have an extraordinary understanding of the mission related information (Mission, Enemy, Troops, Terrain, Time, and Politics) under varying circumstances. Unfortunately, this dynamic is so context-dependent that units typically do not learn the rules until they are already deployed to the mission. Current research in this field indicates that the best solution to this dilemma is to develop a simple knowledge acquisition system that enables the military analysts to quickly encode knowledge-based rules into a decision support war gaming system after already having deployed to the mission site. The unit personnel must be able to do this without assistance of expensive contracting to civilian knowledge engineers and scientists.

The benefits of using Bayesian probabilities to model uncertainty in decision support are well known [Pearl 1988, desJarins 1993]. The Bayesian probabilities capture many stochastic-process factors. It can be used to predict the effects that changes of certain attributes have on decision processes. For example, consider a Commanding Officer (CO) deciding 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 action will force the enemy to turn away (with a very large probability value) or the enemy will force the ownship 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. Now, 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 cases are not quite tenable within the framework of differential equations here. The situations, however, can be effectively recorded in a Bayesian probability representation and efficiently evaluated.

The Bayesian approach has three distinct advantages over its constraint-based counterpart: (1) conclusions derived from the Bayesian approach are not susceptible to incorrect categorical decisions about independent facts that can occur with data sets of finite size, (2) using the Bayesian approach, finer distinctions among model structures -both quantitative and qualitative- can be made, and (3) information from several models can be combined to make better inferences and to better account for modeling uncertainty. Bayesian probability enables reasoning under uncertainty and combines the advantages of an intuitive representation with a sound mathematical basis. There are several ways of determining the probabilities for the entities in the Bayesian probabilities [Hanks 1994]. One common approach is to use the joint probability distributions of the constituent components such that

$$\mathrm{pr}(y_k) = \prod_{i=1}^{l} \mathrm{pr}(y_{ik} \mid \pi_{ik});$$

where y_k is a random variable representing the truth value of a proposition (a belief or an action alternative). The y_{ik}s are the possible states of y_k, and π_{ik}s are possible states of a set of independent random variables y_k. 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. The attributes of relevant data objects and the relations are explored in a decision support process using Bayes' rule:

$$\mathrm{pr}(y_k \mid \Pi_k, \xi) = \frac{pr(\Pi_k \mid y_k, x)\, pr(y_k, x)}{pr(\Pi_k \mid x)};$$

where $\Pi_k = \{\pi_{1k}, \pi_{2k}, \ldots, \pi_{lk}\}$ and ξ denotes the background knowledge. 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 combination [Bogler 1987, Baenett 1991]. It gives us a basic computational scheme for evaluating the certainties of data sets from multiple information sources and feeding them into the Bayesian probability computations for evaluating and selection of action alternatives in a submarine tactic decision process.

We illustrate the Bayesian probabilities in the framework of state evaluations in differential games by continuing the use of the example situations described above. That is, consider the problem of ownship chasing a hostile submarine while avoiding being detected in an open sea area. Let's set the situation to the track submarine's navigation speed in the course of tracking. The situation can be described by a decision tree as the one depicted in figure 1.

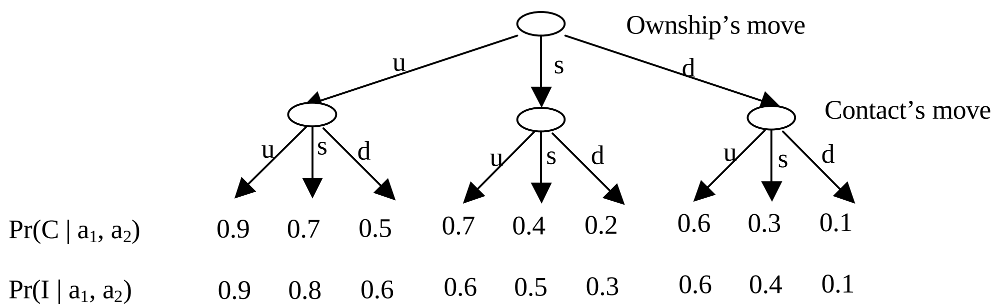

Figure 1. A decision tree model for probabilistic evaluation of game states

In the figure, symbols "u", "s" and "d" stand for speeding "up", "stay the same", and "down" respectively. The $Pr(C \mid a_1, a_2)$ gives an estimation of the probability value such that the two units may collide (or been detected by the contact) based on their combined actions a_1 and a_2 in current situation, where $a_1, a_2 \in$ {"u", "s", "d"}. The probability value is calculated by a pre-defined evaluation function $\eta_i(t, x(t))$ in the differential game model. The $Pr(I \mid a_1, a_2)$ gives an estimation of the probability value that the ownship will still keep in tackle with the contact based on the given actions a_1, a_2 and a pre-defined evaluation function $\eta_j(t, x(t))$. One possible solution for the ownship to decide in above situation is to chose an action among the three alternative such that it will maximize the probability of keep in tackle with the contact and minimize the probability of leading to a collision (or been detected).

To make a probabilistic evaluation of action alternatives, a number of probability values need to be known or obtained before hand. A learning and adaptive module will fulfill this task. The probabilities could be presented in the form such as "the probability of recommending action A under the conditions that …. " and " the probability of achieving objective X under the conditions of specific objective priority." The Bayesian probability operators of the system tries to answer these questions by an outcome-based evaluation – probability estimation based on multiple possible outcomes. The computation is described as the follows.

Let's assuming that there are equal chances for both ownship and the contact to choose an action among the three alternatives. That is $Pr(u_1) = Pr(s_1) = Pr(d_1) = 1/3$ and $Pr(u_2) = Pr(s_2) = Pr(d_2) = 1/3$; where $Pr(u_1)$, $Pr(s_1)$, and $Pr(d_1)$ stand for the probability that the wonunit will choose the actions of "u", "s" and "d" respectively. The $Pr(u_2)$, $Pr(s_2)$ and $Pr(d_2)$ are the corresponding probabilities for the contact. One critical problem in the ownship's decision making is to predict the counter action of the contact. This uncertainty factor can be well represented by probability estimates $Pr(a_2 \mid a_1)$, where a_1 stands for an action chosen by ownship and a_2 the counter action by the contact. For example, we may have the probabilities $Pr(a_2 \mid a_1)$ from an estimation or previous experience, as listed in the table below.

$Pr(a_2 \mid a_1)$	$a_1 = u_1$	$a_1 = s_1$	$a_1 = d_1$
$a_2 = u_2$	0.9	0.5	0.1
$a_2 = s_2$	0.5	0.9	0.5
$a_2 = d_2$	0.5	0.2	0.75

The Bayes' probability rule stipulates the following computations.

$$Pr(C, u_1, u_2) = Pr(C \mid u_1, u_2)\, Pr(u_1, u_2) = Pr(C \mid u_1, u_2)\, Pr(u_2 \mid u_1)\, Pr(u_1)$$
$$= 0.9 \text{ x } 0.9 \text{ x} 0.33 = 0.2673$$
$$Pr(C, d_1, s_2) = Pr(C \mid d_1, s_2)\, Pr(d_1, s_2) = Pr(C \mid d_1, s_2)\, Pr(s_2 \mid d_1)\, Pr(d_1)$$
$$= 0.3 \text{ x } 0.5 \text{ x} 0.33 = 0.0495$$
$$Pr(I, u_1, u_2) = Pr(I \mid u_1, u_2)\, Pr(u_1, u_2) = Pr(I \mid u_1, u_2)\, Pr(u_2 \mid u_1)\, Pr(u_1)$$
$$= 0.9 \text{ x } 0.9 \text{ x} 0.33 = 0.2673$$
$$Pr(I, d_1, s_2) = Pr(I \mid d_1, s_2)\, Pr(d_1, s_2) = Pr(I \mid d_1, s_2)\, Pr(s_2 \mid d_1)\, Pr(d_1)$$
$$= 0.4 \text{ x } 0.5 \text{ x} 0.33 = 0.066$$

… …

The above illustrated probabilistic evaluation of action alternatives is part of the Bayesian operators to be applied in the submarine tactical decision making under a number of specific state determinations. The computation is conducted on the basis of distinguishing different states for taking different decision strategy. The computation can be carried out by taking considerations of the state determinations such as (1) open-loop where the contact has no knowledge about ownship, so will act in its scheduled path and won't count-reacting to ownship's maneuver, or (2) closed-loop where contact also known ownship and will counter-react to ownship's actions.

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 [Harsanyi 1967]. The approach involves introducing some random events (variables) e_i, f_i, i = 1, … N, assumed to occur before the players choose their strategies. The random event e_i will determine player i's cost function and other resources; and so will completely determine the payoff function U_i in the game. On the other hand, the random event f_i will determine the amount of information that player i will obtain about the cost functions and other resources of the other player j ($j \neq i$), and will thereby determine the actual amount of information that player i will have about player j's payoff function U_j. Both players will be assumed to know the joint probability distribution $R^*(\{ e_i \}, \{ f_i \})$. 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 wxactly how much information the opponent will have about him.

An important criteria for this system is the extent to which human-agent interactions support the human operators performance and effectiveness. Therefore, it is important that the way that the agents present information (in their advisory capacity) should be adapted to the human operators needs and goals. Therefore, several different types of formats need to be made available to meet the needs of the uses.

4 Agent Architecture for the Hybrid Model of Decision Support

4.1 Agent-based system architecture

We start with a description of different components of our solution for tactic decision aid under overwhelming information inflow and uncertainty. Figure 2 below shows an initial visual representation of the major system components between the submarine unit command office and an Intelligent Agent (IA)-based knowledge acquisition/decision support system.

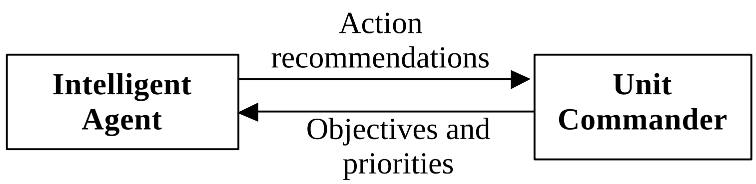

Figure 2. Intelligent Agent model of automated knowledge acquisition and decision support

The need for an Intelligent Agent (IA) is manifest because the various tasks to be performed by the function block (information gathering, analysis, fusion, evaluation, reasoning, etc.). Game theory needs to be incorporated into the IA so that it can be applied during the reasoning stage to produce better plans and action choices. There are four major components in the Intelligent Agent as shown in figure 3. These components are: (1) Information Manager, (2) Reasoning Engine, (3) Adaptation module, and (4) State Control module.

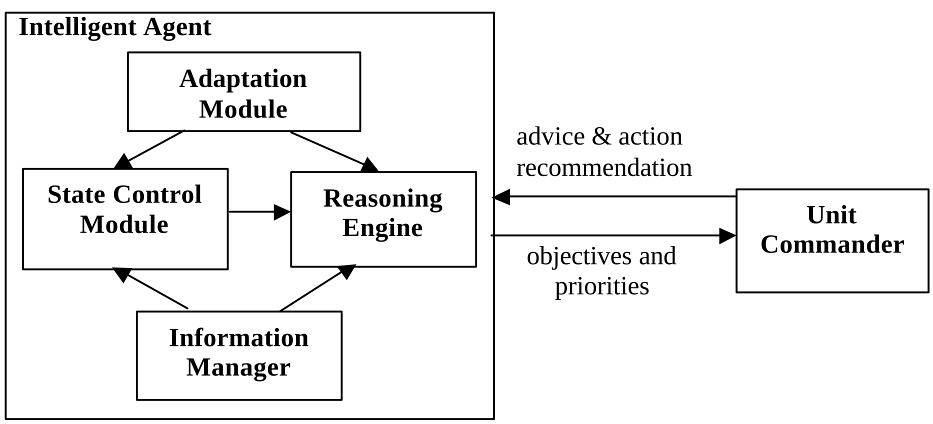

Figure 3. Block diagram of the decision support system

The *State Control module* constantly evaluates the available information about contacts and computes the probabilities on each of the objectives such as whether own unit is detected by the contacts or not. A set of states is defined to span the possible states of engagement and include, for example, initial detection/response, contact trail, track contact, close contact range, contact avoidance, contact prosecution, etc. The Agent upon the detection of a new contact starts the algorithm in the initial detection/response state where the overriding concern is to prevent collisions with contacts and conduct a maneuver to place *Ownship* into the optimal tactical advantage. Based upon the priorities selected, the state will change such that the actions recommended by the Agent are selected to optimize the desired outcome. The mathematical problem is subject to Stochastic Control Theory. The State Control module determines the state of the encounter through the use of Discriminant Analysis [Nath 1992]. Discriminant Analysis is a standard statistical methodology that uses multiple measurements of an object or situation and classifies it as one of several categories. From this data, the Agent will analyze the situation to recommend the optimal course of actions to achieve the goals. This optimization spans all possibilities and is computationally intensive. If however, realistic constraints are considered a heuristic model of game theory will provide the real time recommendations necessary to the Commanding Officer. Our Agent will employ a stochastic game model and the optimization problem will be handled using Stochastic Control Theory based on Bayesian probabilities.

If the Contact changes course in a manner such that the probability of counter detection is satisfied, the Agent will alert the Commanding Officer and evaluate the situation to provide an optimal recommendation to meet the goals as provided. We must be able to distinguish a "true" change in behavior from a noisy set of data, and this has to be done in the fastest possible way. This problem is subject to Sequential Analysis and is known as the Change Point Problem [Ghosh 1991]. An alternative approach would be to use Discriminant Analysis again, or a combination of these methods considered and evaluated over a period of time. The Agent will continue to provide recommendations to place Ownship into the best tactical position.

The *Information Manager* plays the important role of interfacing the *Ownship's* information sources to the Agent. Data must be filtered and pre-processed so that it is in a form that can be effectively used by the agent. The Preprocessing and Filtering operators are in charge of clearing up the signals received from sensors and compensating for the uncertainty contained in the raw information. This interface will be standardized such that its application can be ported to all classes of submarine missions with minimal installation and special interface cabling.

The *Adaptation module* is an important component that collects the data describing all the contacts and analyzes it to improve the stochastic models, to improve the estimates for our models, to study the distributions of random factors and white noise factors. Various statistical methodologies and data mining techniques will be applied here. The adaptive system module will apply previously captured knowledge through experience or decoded from known submarine operation rules to initialize the parameters of the differential game model and Bayesian probabilities. It can also make dynamic updating of these parameters. By activating the adaptive module, the a priori probabilities and the conditional probabilities of the Bayesian decision model are established, obtained, and refined. The presence of the Adaptive Component in our system architecture would allow us to improve the performance of the Agent with time.

The *reasoning engine* applies Bayesian and differential game-theoretic operators to solve the optimal control problem for the submarine operations in various states. In our mixed strategy of decision aids, the solution to these states is reduced to solving a set of differential equations associated with probability evaluations. The process is a result from the optimization problem constrained to the set of stochastic kinematical differential equations describing the types of contacts. A number of related problems have been solved by similar means, for example maritime collision avoidance, missile chasing a plane, simultaneous confrontation of two planes etc.

4.2. *AEDGE™ Implementation*

The Submarine Tactical Decision Aid is implemented using 21CSI Inc.'s Agent Enhanced Decision Guide Environment (AEDGE™). The AEDGE™ product is based on an extensible architecture and a number of standard components that enable simulation and decision support capabilities. This marriage of the Decision Aid to a COTS based decision support architecture will ensure standardization and portability of the decision aid throughout its development [Petrov 2000, Hicks 2001]. Below is a brief outline of the AEDGE™ and capabilities.

The AEDGE™ employs a well-modeled class and object hierarchies (multiple inheritance) to support active entities (agents of different types, simulation objects as well as functional objects) communicating over a software bus, cooperating and so on. Services and libraries to support various analyses tasks in decision aid are provided. The system was implemented in Java™, with Java Database Connectivity™ for DB access, Java AWT and possibly 3D for interfaces, JFC for common objects and so on. The kernel of the architecture consists of four core and five extender components. These define the internal structures, dataflow, and interface to the architecture. The four core AEDGE™ components are the following:

- *Master Server*. Tracks components and matches service providers with service requesters and facilitates connections and interactions among the rest of the AEDGE™ components. It provides component registration and tracking services, interface matching services and component search, identification and connection services. The Master Server is also responsible for synchronizing simulation time (and real time) among multiple simulation servers and live links.
- *Entity Representation Framework*. Provides the basic entities and events for a time-event simulation or live-feed connections. The object-oriented hierarchy of entities represents a wide range of structures, vehicles, platforms, weapons, and sensors. The Framework includes a number of interfaces, which allow users to add new entities with new behaviors or with combinations of existing behaviors.
- *Agent Infrastructure*. Provides the basic inter-agent communication and synchronization mechanisms, as well as the interfaces for agents to use other data sources, such as simulation servers, live data links, databases, etc. A base hierarchy of agents is also provided and it can be extended and customized for particular user's need.
- *Database Connectivity*. Provides generic and specific bridges to a number of proprietary and public databases, such as Oceanographic Data, Weapons Effectiveness, Vehicle Characteristics and Performance, Intelligence, Rules of Engagement, Weather, etc. New database connectivity modules can be added by extending the provided database bridges and implementing the connectivity interfaces.

In addition to these kernel components, extender components define the basic functionality of information clients and servers and define interfaces for adding new functionality. These components are, in essence, templates for extending the platform with new functionality, while maintaining tight integration and efficient implementation. The following standard AEDGE™ extender packages are provided:

- *Simulation Servers*. Model a particular aspect of the physical reality in terms of the AEDGE™ components. In other words, a simulation server maintains a set of entities (e.g., contacts), their properties (e.g., velocity, tonal information, maneuverability, etc.), and those of the environment and models the interactions among those (e.g., tactical simulation). A simulation server may potentially interact with all four core components of AEDGE™. It registers with the Master Server and posts its exported services (e.g. providing entity position information). The server manipulates a set of entities (object instances) from the Entity Framework that represent the current view of the world according to that simulator. The simulation server may interact bidirectionally with agents from that Agent Infrastructure, both providing information about the state of the world and receiving recommendations and action requests from Agents

- *Live Links*. Based on sensor information and reflects the state of the physical world in real-time and thus, the information flow in unidirectional. The live links may provide entity or track information, weather information, or any other state or capability changes. The links can interface with all core AEDGE™ components, much like the simulation servers can, with the limitation of unidirectional communication.
- *Visualization Clients*. Responsible for interactions with the human users. They present visual/auditory data from the AEDGE™ in a clear and intuitive manner, allowing for simple, yet powerful presentations of complex interdependencies in the simulated/sensor world. Visualization clients interact with all components of AEDGE™ through bidirectional information flows. They receive information on the simulated entities, their environment and interactions, as well as on agent evaluations and recommendations. The users' interactions with the Visualization client provide feedback, which is then sent back to the AEDGE™ core components.
- *Agent Clients*. Host one or more Intelligent Agents, which monitor the simulated world, react to changes in it, and interact among each other and with human users according to their specific agent behaviors. The agent client receives information from the AEDGE™ core on the state of the world and sends back agent requests and feedback.
- *Database Bridges*. Natural extension of the AEDGE™ core Database Connectivity. Bridges to characteristics and performance data, weapons performance and effectiveness data, and terrain databases are provided. Interfaces for new database bridges are also provided.

5 Conclusion

This paper explores the problem of providing tactical decision support to a submarine CO from the perspective of two fundamental theories and their complementary roles in decision science: the differential game theory and the classic Bayesian probability theory. The paper focused on an effort aimed at alleviating the problems of decision aid under uncertainty through cooperative software enterprise (agents) that integrates a set of game theoretic modeling and stochastic reasoning techniques for the building of man effective knowledge acquisition tool to support military unit tactical decision making in time-critical missions. A COTS based architectural framework was chosen and will be implemented using 21CSI's Agent Enhanced Decision Guide Environment (AEDGE™). To date, the culminating effort has been the research of the submarine tactical problem domain as well as the theoretical basis behind the differential game and Bayesian probability theories. The system could enable military analysts and planners within a unit to enter directly into a game theoretic decision support tool the domain knowledge such as entities and agent-based rules about entity interaction. The decision support tool that receives the new domain knowledge will be able to provide comprehensive insight to the action/reaction dynamic between the deployed unit and potential adversaries with respect to the employment of resources.

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