On-Line Situation Assessment for Unmanned Air Vehicles

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Abstract

Future conflicts may involve composite striker packages composed of manned and unmanned air vehicles (UAVs) supervised by mission controllers. Since situation awareness (SA) contributes to and is a crucial part of mission success, significant effort is now being placed on developing new technologies that have the potential of increasing SA for the mission controller. This paper describes the design and development of an on-line situation assessment model for unmanned air vehicles that is based on human behavior representation (HBR). The essential feature of this model is its organization around the skilled human's *situation assessment* behavior in a complex multi-task environment. Simulation results are presented for a SEAD mission.

1. Introduction

Unmanned aerial vehicles (UAVs) have been in the US Air Force arsenal since the mid- to late 1950s. Recently, there has been a renewed interest in UAV technology and roles. For example, in 1998 the USAF and DARPA jointly began a program to build and test an Uninhabited Combat Aerial Vehicle (UCAV). Designated the X-45, the goal of this program is to demonstrate the technical feasibility for a UCAV system to effectively and affordably prosecute the 21st century Suppression of Enemy Air Defense (SEAD) mission within the emerging global command and control architecture. As envisioned by DARPA, an operational vehicle of this type would be available in the post-2010 time frame and would be used extensively during the high-threat, early phase of a campaign.

To reduce costs, a single mission controller would receive and process data from multiple UCAVs as well as other national assets (e.g. satellites and AWACS) and simultaneously direct (supervise) the flight team (Kandebo, 2000). Although this concept of operations may reduce costs, it also will create a number of new challenges for maintaining situation awareness (SA) for human pilots and mission controllers. For example, from a control perspective it will be difficult for a mission controller to maintain SA for each UCAV as well as for the overall mission. This is due to information overload caused by the need to quickly and accurately monitor large amounts of data under time-stressing conditions as well as the need to understand the autonomous capabilities of the UCAVs.

From past experience with manned air warfare scenarios, it is well known that fighter pilots make dynamic decisions under high uncertainty and high time pressure. Under such conditions, numerous empirical studies (Stiffler, 1988) and pilots' own accounts (Singleton, 1990) indicate that the most critical component of decision-making is SA, obtained via the rapid construction of tactical mental models that best capture or explain the accumulating evidence obtained through continual observation of the tactical environment. Once a mental picture is developed, decisions are automatically driven by the selection of pre-defined procedures associated with the recognized tactical situation. Such SA-centered decision-making, sometimes called recognition-primed decision-making (Klein, 1989a), has been widely accepted as the most appropriate representation of actual human decision-making in high tempo, high value situations (Klein, 1989a & Endsley, 1995b).

For UCAV or UAV-based missions, the importance of accurate and timely SA will be no less demanding than human-only based missions. In fact, a number of new challenges for maintaining SA exist, including: 1) development of autonomous SA algorithms for the unmanned vehicles to drive their decision logic, 2) fusion of each strike package element's SA information at the mission controller's workstation (or cockpit), to create a global picture of the battlespace, and 3) interpretation of the fused SA information in a manner that supports optimal mission planning, re-routing, targeting, and threat evasion. The objective of the current research is to develop an on-line SA model to alleviate some of the aforementioned problems. This paper describes the design and development of this model.

2. Background

This section provides background material that supported the modeling and development effort. Section 2.1 describes the Rasmussen Hierarchy of human information processing and skilled behavior, which is a conceptual framework for analyzing different types of human skills. Section 2.2 describes past research in the area of human decision modeling that supported the formulation of the intelligent agent model. Finally, section 2.3 describes SAMPLE, an in-house agent developed for SA.

2.1 Rasmussen Hierarchy of Human Behavior

Rasmussen's three-tier model of human information processing and skilled behavior (Rasmussen, 1981 &

1982), shown in Figure 1, provides a good unifying theoretical framework for analysis of different human skills that may be modeled within a real-time simulation. By dividing skilled behavior into categories based on the degree of automaticity, complexity, and level of cognitive processing, this framework supports systematic skill decomposition and measurement of individual aspects of the overall skill on a part-task basis.

Each link in Figure 1 represents flow of information through the human information processing apparatus. Information flows through the system starting at the bottom left with environmental input, and flowing upwards along the left side of the diagram to the most complex level of knowledge-based processing.

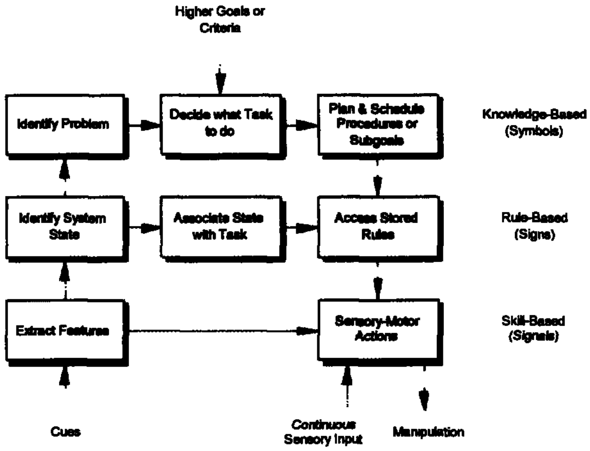

Figure 1: Rasmussen Hierarchy of Human Behavior

Decisions about behaviors propagate downward through the right side of the figure until the motor organs execute them. Aspects of the stimuli that can be handled at the lower levels are processed there (i.e., a cognitive "shortcut") and only situations that require more sophisticated processing reach the most complex knowledge-based level. Processing is divided into three broad categories, corresponding to activities at different levels of complexity:

1. **Knowledge-based behavior** is the highest level of complexity and is required for any complex problem solving that has not been fully automated. It typically involves handling new or unusual situations where reasoning from first principles is required. These situations are often made more complex by the need to engage in several parallel tasks simultaneously.
2. **Rule-based behavior** is at the core of high-performance skill. It involves well-practiced, often highly automatized behavioral sequences that comprise a set of *compiled situation-action pairs* (i.e., rules). It is demonstrated in situations requiring standardized procedures. The emphasis here is on accurate and timely situation assessment, followed by the appropriate procedural response.
3. **Skill-based behavior** involves well-practiced sensorimotor skills that do not involve cognitive resources, but are performed largely automatically in response to recognized stimuli. It is the most automated type of behavior demonstrated by almost unconscious performance of highly trained sensorimotor tasks.

The Rasmussen hierarchy is a good framework for decomposing a particular task-skill pair into constituent skill-types, each with different processing characteristics and requirements. Although not posed directly as a computational representation, it does provide a good basis from which to approach the design of an intelligent agent for human behavioral modeling.

2.2 Human Decision-Making in Complex Task Environments

Human performance in decision-making has been studied extensively, primarily through empirical studies but increasingly with computational tools. These studies span the theoretical-to-applied spectrum and cover many domains. For example, Endsley (1995a) and Adams, Tenney & Pew (1995) discuss a psychological model of decision-making, focusing in particular on situation awareness (SA), and the impact of particular system characteristics on the operator workload, attention and memory requirements, and the likelihood of errors.

Klein (1994) has studied a particular type of decision-making predicated on the quick extraction of salient cues from a complex environment and a mapping of these cues to a set of procedures. Research indicates that such *Recognition-Primed Decision-making* (RPD) plays a major role in planning and it is therefore critical for decision-aiding systems to recognize and support this mode of human information processing. Situation-centered decision-making has been widely accepted as the most appropriate representation of actual human decision-making in high tempo, high value situations (Fracker, 1990). Accordingly, the development of appropriate human behavior representations should be based on the development of realistic SA models.

2.3 SAMPLE: A Computational Model for Human Behavior Representation

Figure 2 shows the underlying architecture used to develop an on-line SA model for unmanned vehicles. Called SAMPLE, this architecture combines elements of the Rasmussen Hierarchy and the Crew/System Integration Model (CSIM) (Zacharias et al, 1981, and 1996). Specifically, it integrates the information processing, situation assessment, and decision-making concepts of CSIM with the explicit delineation of skill based and rule-based behavior of the Rasmussen Hierarchy.

Two branches exist underneath the sensory channels and attention allocation block. The "shortcut" between continuous input filtering and the control channel serves the same function as the skill-based branch of the Rasmussen Hierarchy, while the path beginning with feature extraction and ending below the procedure selector is the equivalent of the rule-based branch. Like CSIM, a modeled behavior is that of directed attention allocation or situation assessment.

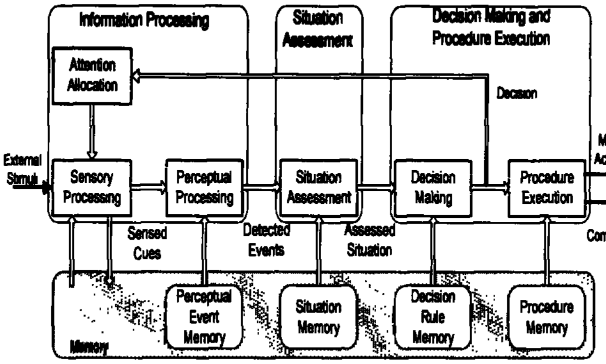

Figure 2: SAMPLE Agent Model Architecture

Development of an on-line situation assessor called for computational intelligence that integrates several enabling technologies to implement the essential functions performed during real-time situation assessment: event detection, situation assessment, and decision-making. In past efforts, e.g. Mulgund et al, 2000, we have demonstrated the capabilities of three key technologies for carrying out these functions: fuzzy logic, belief networks, and expert systems.

First, **Fuzzy logic** (FL) is used to implement a "front-end" event detection module. This module transforms fused sensor data into situationally relevant semantic variables that, as a group, define the overall tactical situation.

Next, **Belief networks** (BNs) (Pearl, 1988) are used to compute situation assessment. BNs combine the detected events with one or more structural models of the environment, to provide a probabilistic assessment of the situation in the presence of uncertainty, and the prediction of expected events consistent with that situation. BNs emulate a skilled human's information fusion and reasoning process in a multi-task environment and provide a comprehensible picture of the SA problem by indicating the dependent relationships among the high-level (symbolic) variables and low-level (numeric) variables. This provides a clearer view (than a low-level neural network-based approach would, for example) of how each individual piece of evidence affects the high-level tactical picture.

Finally, **Expert Systems** are used for decision-making. Human decision-making is modeled using a cascade of two sub-models: a procedure selector and a procedure executor. In tandem, these emulate a human's rule-based decision-making behavior and psychomotor skills in executing a selected procedure. Decision-making behavior is implemented as a production rule system that supports selection of a procedure set that is pre-assigned to the assessed situation specified in the human operator's mental model. Details of the procedure set, and its linkages to the associated situation, are maintained in a procedural knowledge base.

3. Application to Unmanned Vehicles

3.1 Mental Model Development

This work is an extension of prior work done by Mulgand (1997). A SEAD mission was chosen to demonstrate the on-line situation awareness model. The information processing, situation assessment, and decision-making models required to implement the SAMPLE agent were developed via an extensive knowledge engineering and cognitive task analysis (CTA) effort conducted with an experienced USAF pilot. CTA determines the mental processes and skills required to perform a task at high proficiency levels (Redding, 1992).

To identify the information requirements, a goal-directed task analysis based on the methodology of Endsley (1993) was done. The SA information requirements were defined as those dynamic information needs associated with the major goals or sub-goals, which a SEAD vehicle (piloted or un-piloted) must perform. Three steps were involved in identifying these needs. First, the major goals of the job were established, along with the major sub-goals necessary for meeting each of these goals. Second, the major decisions associated with each sub-goal, that needed to be made, were identified. And third, the SA information requirements for making these decisions and carrying out each sub-goal were then identified. These requirements focused not only on what data are needed, but also how that information was integrated or combined to address each decision.

The knowledge engineering effort yielded a network representation for the mental model of a pilot executing a SEAD mission. Key situation awareness variables included vulnerability, ability of completing mission, sort plan effectiveness, likelihood of getting hit, projected time on station (TOS), and threat level (Hanson & Harper, 2000). An unmanned vehicle then uses this network to obtain human-like reasoning. In general, the network consists of a large set of interconnected nodes, each representing a different event detection, situation assessment, and decision-making function. Figure 3 illustrates one of the belief networks in the overall SA network. This BN computes the threat level "experienced" by the unmanned vehicle as it flies in enemy territory. Threat level assessments drive decisions regarding which threats to engage, when to engage a threat, and self-vulnerability. This diagram shows that to first order, threat level causally depends on three quantities:

- threat disposition – is the threat aggressive or passive?
- ownship ability to counter the threat – can I evade the threat using terrain, electronic counter measures or maneuverability?
- ownship position in the threat weapons employment zone (WEZ) – am I in-range, near the edge, out of range?

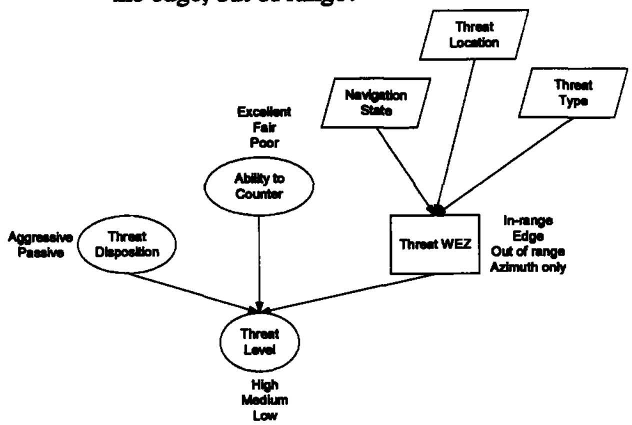

Figure 3: Example Belief Network: Threat Level Assessment

Threat Disposition and Ability to Counter are the outputs of other belief networks not shown. Whether or not the vehicle believes it is in a threat's WEZ depends on three factors: vehicle position and navigation state, the threat location, and the type of threat, e.g. a SA-2 or SA-10. Because this assessment is not a probabilistic inferencing process, it cannot be represented directly with a belief network. Instead a mathematical algorithm, based on assumed threat parameters such as maximum range and maximum altitude, estimates ownship position with respect to the WEZ. Fuzzy logic is then used to incorporate uncertainty due to inexact values in the threat parameters and position.

3.2 Simulation Results

To demonstrate the on-line SA model, simulations were done using a modified version of the Man-In-the-Loop Air-to-Air System Performance Evaluation Model (MIL-AASPEM), developed by The Boeing Company (Lawson & Butler, 1995). MIL-AASPEM is a high-fidelity simulator used extensively for subsystem effectiveness evaluation and air combat tactics development. It includes capabilities for representing multiple types of aircraft and their associated avionics, sensor subsystems, displays, weapons and ground players.

All trials used two UCAVs beginning roughly 60 NM due West from the striker's target. Figure 4 shows a birds-eye view of the situation. The nominal UCAV flight paths are shown in red and green. The striker flight path is shown in blue. The UCAVs fly to station points and then fly radar minimization arcs (shown as circles). The integrated air defense systems (IADS) consisted of four surface-to-air missile (SAM) sites. Maximum WEZs for the sites are shown as black circles. The striker target is located well inside the IADS at coordinates (0,0).

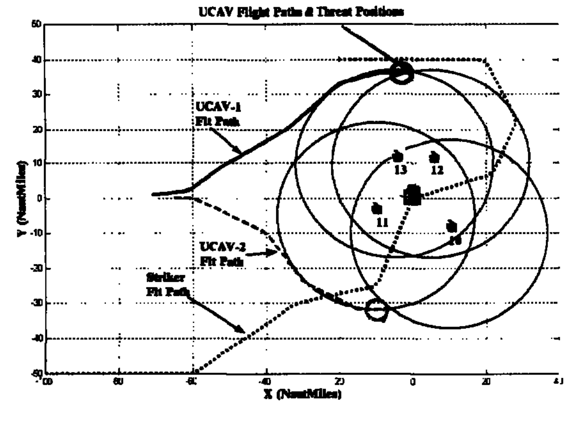

Figure 4: Bird's Eye View of Scenario

Figure 5 show threat level assessments made for each of the three vehicles as a function of the X and Y positions. These values were generated by "flying" each vehicle on its desired flight path and using onboard sensor measurements, e.g. radar warning receivers, to obtain data needed for the threat level belief network. The single numbers shown for each vehicle result from converting the high, medium, and low states into a scalar ranging from 0 (no threat) to 1 (high threat).

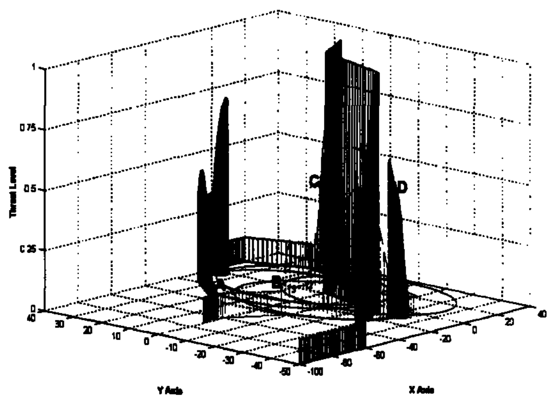

Figure 5: Assessed Threat Levels (red = UCAV-1, green = UCAV-2, and blue = Striker)

Inspection of the figure shows that at long ranges, the perceived threat level on all vehicles is low. This is expected since the vehicles are out of the threat WEZ. As the vehicles approach the IADS sites, the threat levels vary depending on the range to the threat and the aspect angle between the vehicle velocity vector and the radar beam. For instance, the threat level on UCAV-2 (shown in green) is constant (see A on figure) until the vehicle nears the perceived edges of the SAM WEZs (B). The threat level begins to rise and fall (C) as the vehicle tries to fly 90° to the radar beam of SAM-site 11, which increases the beam aspect angle on SAM-site 12. The perceived threat level drops, and then enters a cyclic pattern (D) when the vehicle reaches the station point and begins its orbit (flying into and out of the threat WEZs.

4. Summary

The design and development of an HBR-based intelligent agent model for on-line situation assessment has been described. This agent model uses fuzzy logic for event detection, a probabilistic representation of human information processing and situation assessment as the foundation for modeling complex decision-making behavior in multi-task environments, and expert systems for decision-making. The agent was implemented in an on-line situation assessor for mission controllers to facilitate situation awareness and increase controller effectiveness. Using a SEAD mission, the utility of this agent for modeling and calculating tactical piloting behavior for unmanned vehicles was shown. Current research is directed towards implementing an intelligent on-board vehicle controller that uses the agent to make human-like decisions and execute the mission.

Acknowledgments

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