OLIPSA: ON-LINE INTELLIGENT PROCESSOR FOR SITUATION ASSESSMENT

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ABSTRACT

This paper describes a study that assessed the feasibility of developing an concept prototype for an On-Line Intelligent Processor for Situation Assessment (OLIPSA), to serve as a central processor to manage sensors, drive decision-aids, and adapt pilot/vehicle interfaces in the next-generation military cockpit. The approach integrates several enabling technologies to perform the three essential functions of real-time situation assessment:

- Event detection uses a fuzzy logic processor and an event rulebase to transform fused sensor data into situationally-relevant semantic variables.
- Current situation assessment is performed using a belief network (BN) model to combine detected events into a holistic "picture" of the current situation, for probabilistic reasoning in the presence of uncertainty.
- Future situation prediction is carried out via case-based reasoning, to project the current situation into the future via experience-based outcome prediction.

The prototype OLIPSA was developed in object-oriented C++ and integrated with a flight simulation model on an SGI workstation. OLIPSA's performance was demonstrated initially in the defensive reaction portion of an air-to-ground attack mission, in which a pilot must deal with an attack from threat aircraft. Situation awareness models were developed to support the pilot's assessment of the threat posed by detected aircraft.

INTRODUCTION

Air combat demands that pilots make dynamic decisions under high uncertainty and high time pressure. Under such conditions, numerous empirical studies (Stiffler, 1988) and pilots' own accounts (Shaw & Baines, 1988; Baker, 1986; Singleton, 1990) indicate that the most critical component of decision-making is situation awareness (SA), obtained via the rapid construction of tactical mental models that best explain the accumulating evidence obtained through continual observation of the environment. Once a mental "picture" is developed, decisions are automatically driven by the selection of pre-defined procedures associated with the recognized tactical situation. This is SA-centered decision-making (sometimes called recognition-primed decision-making or RPD), and it has been widely accepted as the most appropriate representation of actual human decision-making in high tempo, high value situations (Endsley, 1989; Endsley, 1990; 1993;Endsley, 1995b; Fracker, 1990; Klein, 1989a; Klein, 1994; Stiffler, 1988).

As a result, improving pilot SA in air combat has become a principal goal of the Human Systems Technology Investment Recommendations made by USAF's Development Planning Directorate (Development Planning Directorate, 1995). Many new technologies and subsystems are being considered to enhance pilot SA. The problem is not one of a lack of subsystem development efforts; rather it is the lack of an integrated approach to delivering this information to the pilot in a more holistic fashion, and in a manner that reflects the current air combat situation. What is missing is a simplified approach to assessing the tactical situation, so that sensor management, decision-aiding, and pilot/vehicle interface (PVI) management all occur within the overall context set by the assessed situation. What is called for is a computationally intelligent design for an on-line *situation assessment processor*, driving the high-level coordination of all other on-board assets.

The premise of this research is that a situation assessment processor can be developed best by first understanding how the adept *human* pilot accomplishes on-line situation assessment, developing a model of that behavior, and then implementing a version of that model using modern computational

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intelligence technologies. Much of the groundwork in the first two areas, understanding and modeling pilot SA, has been conducted over the last decade, and has been extensively reported on in engagement studies (Stiffler, 1988; Hamilton, Dorchak, & Stuart *et al*, 1988), in pilot self-assessment studies (Baker, 1986; Shaw & Baines, 1988; Singleton, 1990), in behavioral studies of the tactical area (Klein, 1989a; Klein, 1989b; Fracker, 1990; Endsley, 1989; 1990; 1993; 1995); and in recent modeling studies (Zacharias, Miao, Riley & Osgood, 1992; Zacharias *et al*, 1996; Adams, Tenney & Pew, 1995). This research facilitates implementation of a *pilot-centered* SA processor that synergistically combines knowledge of how pilots accomplish this task with the new-found ability to host intelligent computing technologies in the modern day cockpit.

Development of an on-line situation assessor for the advanced cockpit calls for an integration of several enabling technologies, implementing the three essential functions performed during real-time situation assessment: event detection, current situation assessment, and future situation prediction. The OLIPSA prototype uses fuzzy logic (FL) to implement a “front-end” event detection module, which transforms fused sensor data into situationally-relevant semantic variables (the essential events that, as a group, define the overall tactical situation). OLIPSA uses belief networks (BNs) to implement a current situation assessment module, which combines the detected events with one or more structural models of the tactical situation, to provide a probabilistic assessment of the situation. Finally, OLIPSA uses case-based reasoning (CBR) to project the current assessed situation into the future, over a tactical time window if interest, to support current assessment of future situations, and subsequent plan development and evaluation. In developing a concept prototype to assess overall feasibility of the approach, an object-oriented design was used for software module specification.

BACKGROUND

The development of an on-line situation assessor may be considered a partial solution to the overall **data fusion** problem. The objective of data fusion is to combine data from multiple sources intelligently, to develop a meaningful perception of the environment (Waltz & Llinas, 1990). While humans have long been able to fuse remotely sensed data using mental reasoning methods and manual aids, in recent years there has been considerable interest in developing automated systems capable of combining data from multiple sensors to derive meaningful information not available from any single sensor. This interest has been motivated by the following concerns:

- Increases in target mobility and weapon lethality demand shorter detection/identification and reaction times
- More complex threats demand improved detection/discrimination capabilities
- Increased personnel costs in some missions have dictated remotely controlled or autonomous weapon systems that require data fusion

These demanding requirements and the increasing complexity of available sensor data exceed the human ability to associate and classify incoming data without decision aids, motivating the automation of various data fusion processes. The Joint Directors of Laboratories (JDL) Data Fusion Subpanel have identified three levels of fusion processing products (Waltz & Llinas, 1990; White & Cohen, 1980):

- **Level 1 DF**: Fused position and identity estimates
- **Level 2 DF**: Friendly or hostile military situation assessments
- **Level 3 DF**: Hostile force threat assessments

Across these levels of *information products*, the generality of the results increases from the very specific (e.g., “missile type A at coordinates B”) to the more general (e.g., “missile attack in progress on city C”). At level 1, numeric procedures such as estimation or pattern recognition dominate the processing operations. Level 1 information products arise from single and multisource processing (such as target tracking) by sampling the external environment with available sensors and other information sources. The products of this processing are position and identity estimates for targets or platforms in the composite field of view (Waltz & Llinas, 1990). Symbolic reasoning processes involving higher levels of *abstraction* and *inference* dominate the level 2 and 3 fusion operations. Situation abstraction is the construction of a generalized situation representation from incomplete data sets to yield a contextual *interpretation* of level 1 products. This level of inference is concerned with deriving knowledge from some type of pattern analysis of level 1 data. The distinction between levels 2 and 3 is that level 3 products attempt to quantify the threat’s capability and predict its *intent* by projecting into the future, whereas level 2 results seek to indicate *current* hostile behavior patterns.

By reviewing conventional definitions of **situation assessment**, it becomes clear that the level 2 and 3 data fusion functions strongly overlap key situation assessment activities. These include (Noble, 1989): 1) an *estimate* of the purpose of activities in the observed situation; 2) an *understanding* of the roles of the participants in the activities; 3) *inferences* about completed or ongoing activities that cannot be observed directly; and 4) inferences about *future* activities. Endsley, 1987Endsley (1995) has also proposed a general definition of SA:

> *Situation awareness is the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future.*

Each of the three hierarchical phases and primary components of this definition can be made more specific: (Endsley, 1995a):

- **Level 1 SA:** Perception of the elements in the environment – This is the identification of the key elements of "events" that, in combination serve to define the situation. This level serves to semantically tag key situational elements for higher levels of abstraction in subsequent processing.
- **Level 2 SA:** Comprehension of the current situation – This is the combination of the level 1 events into a comprehensive holistic pattern, or tactical situation. This level serves to define the current status in operationally-relevant terms, to support rapid decision-making and action.
- **Level 3 SA:** Projection of future status: projection of the current situation into the future, in an attempt to predict the evolution of the tactical situation. This supports short term planning and option evaluation, when the time permits.

A direct comparison of these three levels of SA with the three levels of DF show that the two functions are clearly distinct at level 1, since DF level 1 focuses on the *numeric* processing of tactical elements to subserve identification and tracking, whereas SA level 1 focuses on the *symbolic* processing of these entities, to identify key "events" in the current situation. At level 2 the definitions are virtually identical, concluding with the conventional definition of SA, that of generating a holistic pattern of the *current* situation. At level 3, the SA definition is more general than the DF definition, since the former also includes projection of ownship and friendly intent, whereas the latter only focuses on threat intent. The following integration of the two DF and SA hierarchies are thus proposed, incorporating a single initial DF level to generate estimates of the tactical elements, and three follow on SA levels, to generate key events, current status, and projected future:

- **Level 1 DF:** Fuse position and identity estimates
- **Level 1 SA:** Perceive elements and identify events
- **Level 2 SA:** Assess (comprehend) current situation
- **Level 3 SA:** Project (predict) future situation

This four-level process progressively raises the level of abstraction of the sensor data and pilot knowledge base, to provide a high level holistic view of the tactical situation.

Figure 1 illustrates how the data fusion and situation assessment functions relate to the other key components of an on-board system. We begin with a specification of the external environment. This includes the specification of all friendly, hostile, and neutral forces, as well as a description of the local terrain and current weather conditions. Information on the external environment is sensed by an on-board sensor suite. The Data Fusion Processes fuses this sensor data to generate individual target tracks and to classify and characterize targets. The Situation Assessment Processor uses this fused track data to generate a current situational state from detected events, and then projects the situation to predict future situations. The total situation assessment (events, current situation, predicted situation) feeds higher-level processing for sensor management, threat assessment, decision-aiding, and pilot/vehicle interface (PVI) adaptation. The dotted lines indicate OLIPSA's envisioned scope.

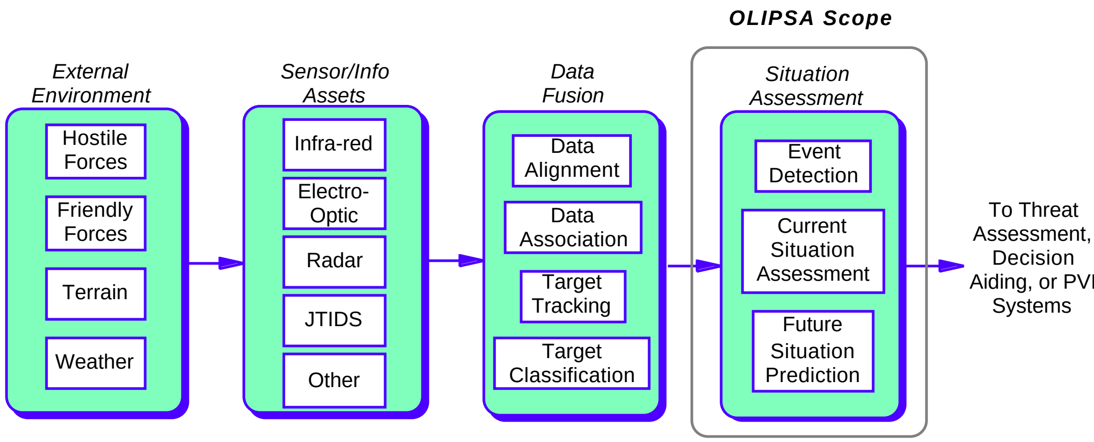


Figure 1. Overall Environment for On-Board Data Fusion and Situation Assessment

OLIPSA FUNCTIONAL DESIGN

Figure 2 illustrates OLIPSA's functional block diagram, which employs a four-stage processor architecture: 1) an event detector; 2) a current situation assessor; 3) a future situation projector; and 4) a context processor. These are described briefly in the following paragraphs.

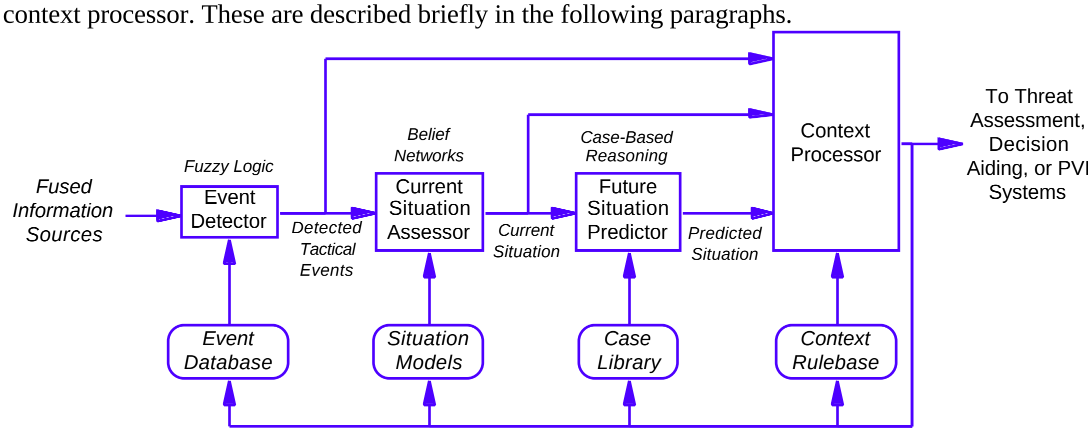


Figure 2. OLIPSA Functional Block Diagram

The **event detector** translates the primarily numerical data generated by the data fusion processor into symbolic data defining key tactical elements. Examples of events are a detection of a threat CAP breaking orbit, a bandit engaging, a mission-related milestone (e.g., crossing the FEBA), or other similar scenario-relevant events that contribute to defining the overall situation. The event detector "engine" can be as simple as a binary threshold logic, converting a numerical value (e.g., threat range) into a Boolean event (e.g., within range of threat envelope). OLIPSA uses a more robust approach to event detection via fuzzy logic (FL) and graded membership functions. Note also the presence of an event database in the figure, which the detector uses to transform scenario states into situation events.

The **current situation assessor** takes in the detected events and generated an assessed situation state $\mathbf{S}(t)$, which is a multi-dimensional vector defining the belief values of a number of possible situations currently facing the pilot. The situations, their relation to one another, and their association with detected events are all defined by a set of situation models, each model being a tree of possible situations and events. OLIPSA employs belief networks (BNs) to implement both the situation models and the situation assessment function. This provides a way of making computationally explicit the extremely complex process of situation assessment in a real-time environment, while at the same time ensuring a fair degree of rigor in inferencing via the use of Bayesian reasoning logic. The net result of this stage of processing is the generation of an aggregated set of situation likelihoods (belief values) and their associated event probabilities, which define the overall situation.

The **future situation predictor** takes in the assessed current situation and generated, over a limited time window, a prediction of the most likely future situations, or $\{\mathbf{S}(t + T), \mathbf{S}(t + 2T), \ldots \mathbf{S}(t$

+ *NT*)}. The output of this block is at the same level of granularity as the proceeding block (i.e., at the situation level rather than the multi-vehicle state level, for instance, but the output future situations are also indexed against future time, from the current time to the end of the limited time window. This provides for a view of how the current tactical situation can be expected to evolve over the time window of interest. The conventional engineering approach for this type of predictor would couple an engagement level simulator with a *current* situation assessor module, and generate, via multiple simulation runs, likely scenarios spanning out into the future. Unfortunately, this is computationally infeasible, given the complexity of engagement level models, and the requirement for real-time on-board operation. OLIPSA employs a computationally less intensive approach via the use of case-based reasoning (CBR), and a well-stocked case library of possible engagement scenarios. This allows OLIPSA to rapidly index the current situation, and on the basis of comparable situations maintained in the library, generate a likely evolution of the current situation, using simple transition rules, at a high level of granularity defined by the situational parameters. The net result is an *experience-based prediction* into the future, with a minimum of computational overhead.

Lastly, the diagram shows a **context processor**, which takes in the outputs of the preceding blocks and generates, via a conventional production rule system, and overall assessment of the situation. This last stage of processing allows for the introduction of additional heuristics not accounted for in the upstream processing blocks, provides for a means of resolving conflicts in the different blocks, and, perhaps most importantly, provides a path by which feedback can be given to the three upstream knowledge bases: the event database, the situation models, and the case library. This feedback path allows for the eventual incorporation of learning and adaptation techniques.

Event Detection using Fuzzy Logic

OLIPSA uses fuzzy logic (FL) technology to implement the event detector module. While some event detection, such as subsystem discretes (e.g., ownship missile launch), can be implemented via simple discrete Boolean logic, most tactically-significant events require a more robust and flexible means of expression. This can be achieved by the use of fuzzy logic.

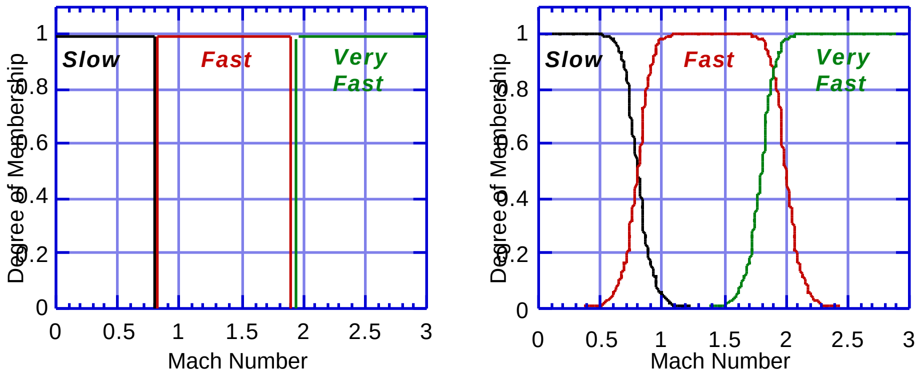
Fuzzy logic was proposed by Zadeh (1965, 1973) as a mathematical concept to deal with uncertainty in human decision-making. He was concerned with how humans can process imprecise non-numerical, or linguistic, information (i.e., *big*, *small*, *very fast*, *heavy*, etc.) to perform a given task. He argued that if a human can perform complex tasks with this imprecise knowledge, then a machine would also benefit from such an approach. Zadeh defined multi-valued or fuzzy sets that are defined by a *membership function*. This membership function relates to or measures the *degree* to which a given element belongs to a set (unlike conventional sets, which specify only whether or not a particular element belongs to some set). Later, he introduced the concept of linguistic variables. For instance the variable pitch attitude could take values of *negative big*, *negative small*, *zero*, *positive small*, *positive big*, etc. Fuzzy logic has been successfully applied in such areas as statistical analysis, pattern recognition, image analysis, robotics, and control theory.

The OLIPSA prototype uses fuzzy logic for deriving the low-level data that feeds the threat assessment network (described below). In the BN formalism, continuous readings must be quantized into one of a finite set of descriptions; for example, speed is characterized as *slow* (Mach 0 to 0.8), *fast* (Mach 0.8 to 1.9), and *very fast* (Mach 1.9 and beyond). However, it is intuitively apparent that there is no meaningful difference between a speed of Mach 0.799 and Mach 0.801. Unfortunately, a BN that uses “hard” boundaries between one category and the next would classify these values as slow and fast, respectively, which might lead to different conclusions regarding vehicle type. Further, if a contact is accelerating or decelerating smoothly, a transition from slow to fast would result in discontinuous jumps in BN output, which may produce undesirable effects.

For example, Figure 5a illustrates the speed classifications using classical, non-fuzzy sets. A given speed measurement may fall into only one of the three categories shown. By contrast, figure 5b shows three fuzzy sets for the classifications *slow*, *fast*, and *very fast.* A given speed measurement is characterized by its degree of membership in each of these fuzzy sets. For example, a speed of Mach 0.8 has a 0.5 degree of membership in the fuzzy set *slow*, and a 0.5 degree of membership in the fuzzy set *fast*. As speed increases or decreases, these degrees of membership change in a continuous manner. This fuzzy characterization has the following benefits:

- The degrees of fuzzy membership are tolerant of noise in the speed measurement
- Similar inputs produce similar outputs, to maintain a smooth, non-jerky response from the BN to time-varying input signals.

• It facilitates knowledge engineering, as it mimics the human approximation process.



(a) Non-Fuzzy Classification (b) Fuzzy Classification

Figure 5. Classification of Threat Speed.

Current Situation Assessment using Belief Networks

The second key component of OLIPSA's architecture is the current situation assessment module, which uses aircraft information system outputs to generate a high-level interpretation of the tactical situation facing the pilot. The OLIPSA prototype relies on belief networks (Pearl, 1988) for reasoning in the presence of uncertainty.

Any robust computational model of situation assessment requires a technology that has: 1) a capability to quantitatively represent the key SA concepts such as situations, events, and the pilot's *mental model*; 2) a mechanism to reflect both diagnostic and inferential reasoning; and 3) an ability to deal with various levels and types of uncertainties, since most real-world systems of any complexity involve uncertainty. Russell & Norvig (1995) cite three principal reasons for this uncertainty:

• *Theoretical ignorance*: All models of physical systems are necessarily approximations.
• *Laziness*: Truly exceptionless rules require numerous antecedents and consequents [cf. 'Frame Problem' (McCarthy & Hayes, 1969) and are therefore computationally intractable.
• *Practical ignorance*: Even if all rules are known, we do not always have time to measure all properties of the particular objects that need to be reasoned over.

The principal advantages of belief networks over other uncertain reasoning methods are:

• Its probability estimates are guaranteed to be **consistent with probability theory**.
• It is **computationally tractable**. Its efficiency stems principally from exploitation of conditional independence relationships over the domain.
• The structure of a BN **captures the cause-effect relationships** that exist among the variables of the domain. The ease of causal interpretation in BN models typically makes them easier to construct (Henrion, 1989).
• The BN formalism **supports many reasoning modes**: causal reasoning from causes to effects, diagnostic reasoning from effects to causes, mixed causal and diagnostic reasoning, and intercausal reasoning. Intercausal reasoning refers to the situation in which a model contains two potential causes for a given effect. No other uncertain reasoning formalism supports this range of reasoning modes (Russell & Norvig, 1995).

Belief networks provide the capability and flexibility of modeling SA with its full richness. They also provide a comprehensible picture of the SA problem by indicating dependent relationships among variables, at both high-levels (symbolic) and low-levels (numeric). This provides a clearer view of how each individual piece of evidence affects the high-level situation characterization. They allow the incremental addition of evidence at any network node as it arrives, thus allowing for real-time SA update. Finally, BNs enable a designer to partition a large knowledge base into small clusters, and then specify probabilistic relationships among variables in each cluster (and between neighboring clusters). This approach facilitates construction of large, robust knowledge bases without explicitly specifying the relationships between all possible combinations of variables. This feature is especially useful for large domains such as tactical situation assessment.

Future Situation Prediction using Case-Based Reasoning

An important component of situation awareness—and a major goal of the OLIPSA system—is the ability to accurately predict, faster than real-time, the evolution of the current situation over some future window of time, in sufficient detail to guide the pilot's decisions. Reliable prediction, even over a time scale of several seconds could provide a significant tactical advantage to a strike package. Furthermore, it is clear that the longer the prediction time, the greater the advantage. However, this is a formidable prediction problem: the multiple-entity air combat environment is a complex dynamic system whose evolution is determined not only by the low-level dynamics of the entities (e.g. aircraft, missiles, etc.) but also by *intelligent* decision-making processes occurring in the minds of the individual combatants and at higher (tactical) levels involving multiple aircraft.

In the development of the OLIPSA prototype, we evaluated the use of case-based reasoning (CBR) for situation prediction. CBR allows us to index the current situation against a library of past tactical scenarios, and on the basis of comparable situations maintained in the library, generate a likely evolution of the current situation, using simple transition rules, at a high level of granularity defined by the situational parameters. The net result is an *experience-based projection* into the future, with a minimum of computational overhead, thus making the approach particularly amenable to real-time implementation with limited computational resources.

A fundamental principle of prediction motivating our approach can be seen in figures 6a and b. Shown are two prediction periods for a given snapshot of a tactical situation. Very simply, the smaller the prediction time, the less important are the inter-entity interactions/relationships that carry a great deal of information about the enemy's tactics and plan. Over very short intervals, the physics of the situation dominates its evolution and individual aircraft trajectories can be computed, to close approximation, independently of each other. Figure 6a depicts this situation: the short gray arrows indicate a small prediction time. As the prediction time increases, the inter-entity information (e.g., the intercept tactic the enemy aircraft are using) becomes the most important factor in predicting the evolving situation. This is suggested in figure 6b, where Dt is larger. Knowledge of the maneuver the enemy is currently employing greatly increases the accuracy and confidence in the predicted state of the system at larger Dt. Thus, to maximize the prediction time and the associated tactical advantage, we should include as much high level information describing inter-entity relationships as possible in the model. The OLIPSA approach is also founded on the following assumptions:

- The air combat situation space can be represented fairly coarsely and still provide highly useful—i.e. mission critical—information on which each combatant can act. This assumption is mandated by the need for real-time performance. If the behavior of all aircraft, missiles, etc. in the scenario must be characterized in great detail, faster-than-real-time predictions will be infeasible. Thus, a fairly coarse discretization of the airspace and of time is necessary.
- Air combat is constrained by tactical principles, in the sense that military pilots undergo extensive training in which the accumulated wisdom and experience are inculcated in them. Thus, we can expect that past scenarios will be good predictors of new engagements.
- The longer the prediction time, the better the plans the pilot can generate.
- Assuming that the threat aircraft are executing some formation tactics, it follows that the movements/actions of any one aircraft will generally be predictive of the movements of the others. In other words, there is a great deal more information—and thus, more predictive power—in the spatio-temporal correlations over the *set* of enemy aircraft than in the individual trajectories viewed in isolation. Dong & Atick (1995) provide analyses showing this is generally true of spatio-temporal image sequences. Accordingly, any proposed prediction system should efficiently represent spatio-temporal context.

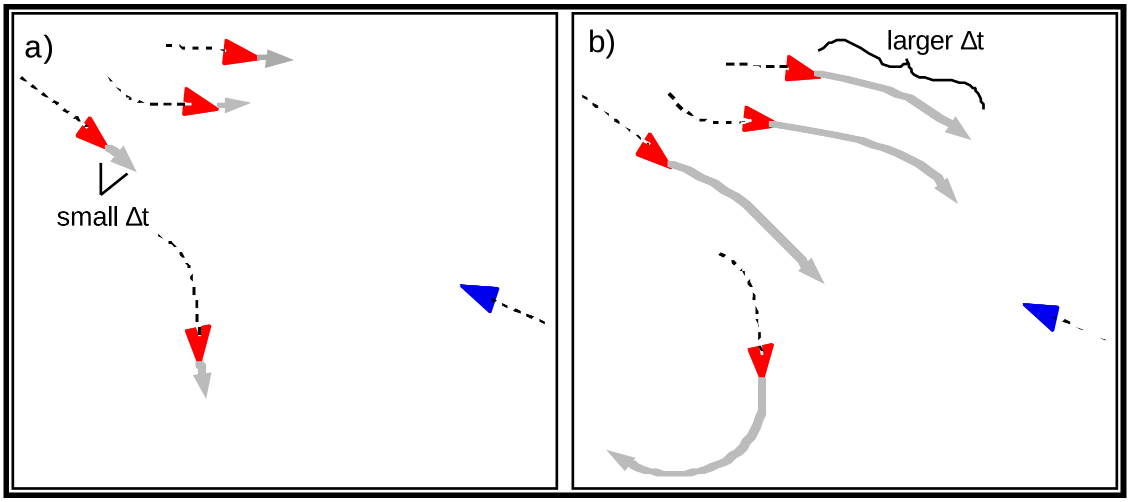


Figure 6. Trajectory Prediction over (a) Short and (b) Long Prediction Time.

OLIPSA IMPLEMENTATION FOR AIR-TO-AIR THREAT ASSESSMENT

The prototype OLIPSA models the threat assessment process that a fighter pilot carries out during the defensive reaction segment of an air-to-ground attack scenario. During this segment of the scenario, the pilot must make a judgment as to the potential threat to ownship posed by an aircraft detected by the onboard sensors, in the overall context of the mission and its rules of engagement. This assessment will support the pilot's decision to attack, avoid, or defend against the detected contact.

Figure 7 illustrates the threat assessment BN we developed through consultation with a subject matter expert. The network quantizes threat potential into one of four categories: *high*, *medium*, *low*, or *none*. The *rectangular* nodes denote information that is derived directly from sensor measurements, while the *oval* nodes denote hypotheses that are computed in accordance with the axioms of probability from this sensor data, using the information stored in the network's conditional probability tables.

The threat potential depends directly on the type of sensor contact (*transport*, *bomber*, *fighter*, or *missile*), its aspect angle (*low*, *medium*, or *high*), its location with respect to our estimate of its threat envelope (*out of range*, *within range*, *inside minimum range*, or *within gun range*), and its maneuvering actions (*turning towards ownship*, *turning away*, or *non-maneuvering*). The *type* and *aspect* hypotheses are integrated into a single super-node called *type and aspect* because fighter aircraft and missiles are a greater threat when pointing directly at ownship, while bombers often have tail guns and therefore are of greater concern when pointed directly away. As such, the effect of aspect angle on threat hypothesis depends on the type of vehicle, making it appropriate to integrate the two variables. The *type* hypothesis depends on the following: 1) the output of ownship's non-cooperative target recognition system (NCTR); 2) the radar type classification generated by the radar warning receiver (RWR), if any; 3) the contact's altitude; and 4) the contact's speed. Contact altitude, speed, and aspect angle are derived using radar system outputs and ownship air-data systems.

In the course of a simulation, multiple copies of this network are instantiated (one for each sensor contact). The threat hypothesis generated by each network drives the radar display symbology, so that display appearance correlates with the hypothesized threat assessment. The intent of this adaptation is to make display symbology relate to the situation, to assist the pilot in assessing which detected contacts pose the most potential hazard to mission completion.

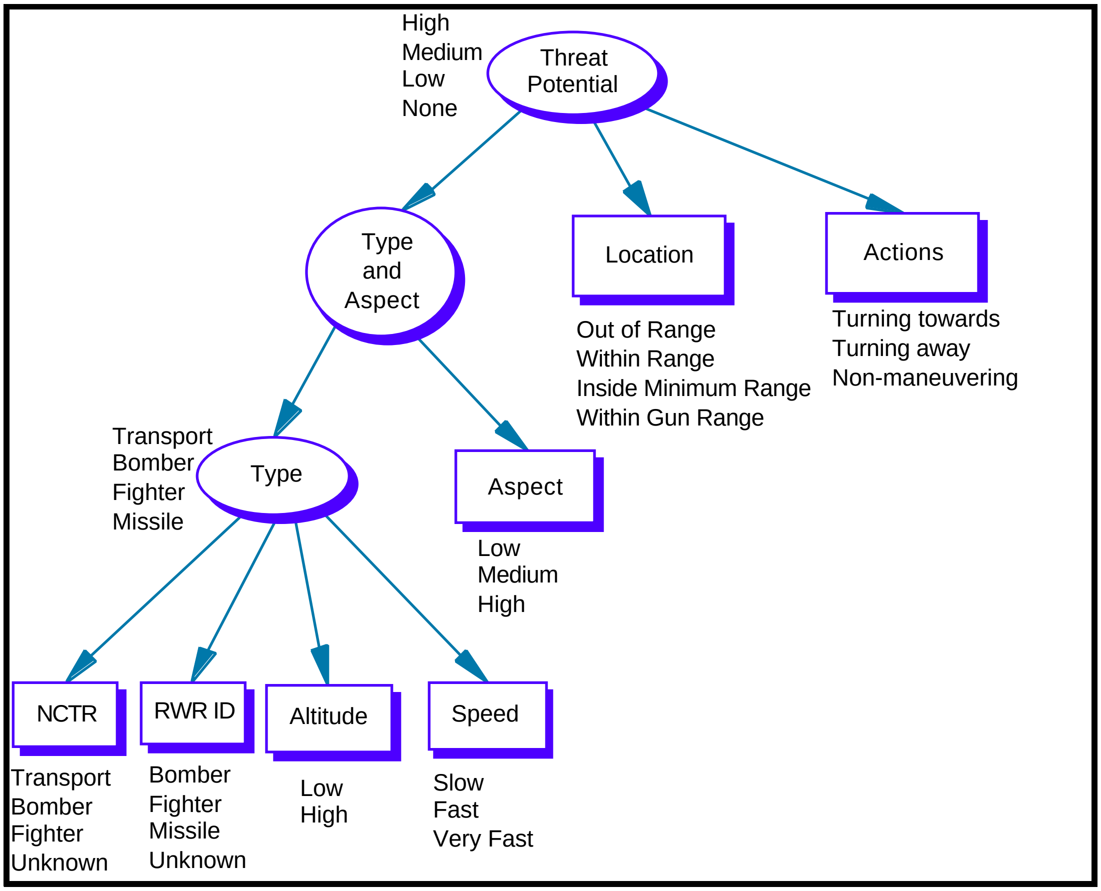


Figure 7. Belief Network for Air-to-Air Threat Assessment.

Figure 8 depicts the sample case structure based on the threat assessment BN developed under this effort. These variables encode an approximate description of each enemy entity's position, aspect, etc. relative to the ownship. Therefore, the entire spatio-temporal vector comprising the case implicitly represents all higher, plan- and tactical-level information present in the system. Other high-level features of the battle scenario may also be included in the case description.

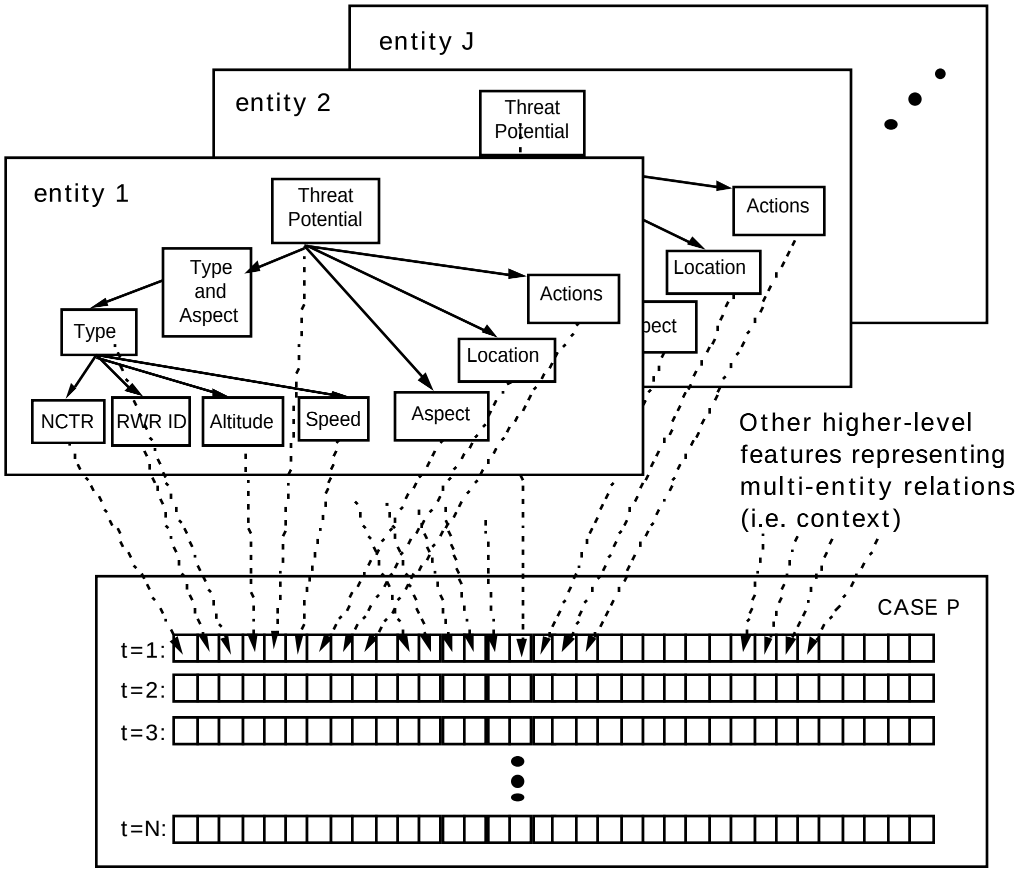


Figure 8. Case Structure For OLIPSA Future Situation Prediction Module.

The prediction module's initial development was carried out using the PC-based *Esteem* CBR development environment. This standalone shell allows rapid creation and analysis of a broad range of case definitions, similarity metrics, and adaptation metrics. In particular, it allows us to compare prediction performance across a range of index set sizes.

The desired output from the prediction module is the most likely evolution of the situation over the next temporal window. Accordingly, the general framework is to compare the vector describing the current situation to the situations stored in the library of past cases, returning the case containing the closest match. For purposes of making the match computation faster, the similarity metric may be defined over a subset of the features rather than all of them. This subset is referred to as the set of index features. This implies less flexibility in the matching process; i.e., less tolerance to missing features. Therefore, some approaches, notably Waltz's memory-based reasoning (Waltz, 1989), include all case features in the index set, thus comprising a very high dimensional *nearest neighbors* technique. Once the closest matching time slice has been found, the remaining time slices in that case are read out as the model's prediction of the scenario's evolution.

OLIPSA-Based System Automation

For initial demonstration of OLIPSA operation, we have developed four levels of SA-driven aiding that are implemented in a prototype air-to-air radar display:

Level 1: Basic air-to-air radar display
Level 2: Graphical radar symbology that incorporates the BN-driven threat assessment, so that symbol coding is proportional to threat hypothesis
Level 3: Augmentation of adaptive graphical radar symbology with audio alerts
Level 4: Adaptive graphical radar symbology, audio alerts, and computer-based control of radar scan pattern as a function of the tactical situation

Level 5: Adaptive graphical radar symbology, audio alerts, computer-based control of radar scan pattern as a function of the tactical situation, and computer takes over task of releasing chaff during missile evasion maneuvers

Figure 9 presents a legend for our air-to-air radar symbol coding, for level 2 aiding. This legend is based in part on the symbology used in the FITE simulator facility at Wright-Patterson Air Force Base (Haas *et al*, 1995). To this we have added the threat potential coding: as the threat potential predicted by the threat assessment BN increases, the symbol line thickness increases in proportion. For a *high* threat, the symbol is drawn completely filled in, to give it the highest possible salience.

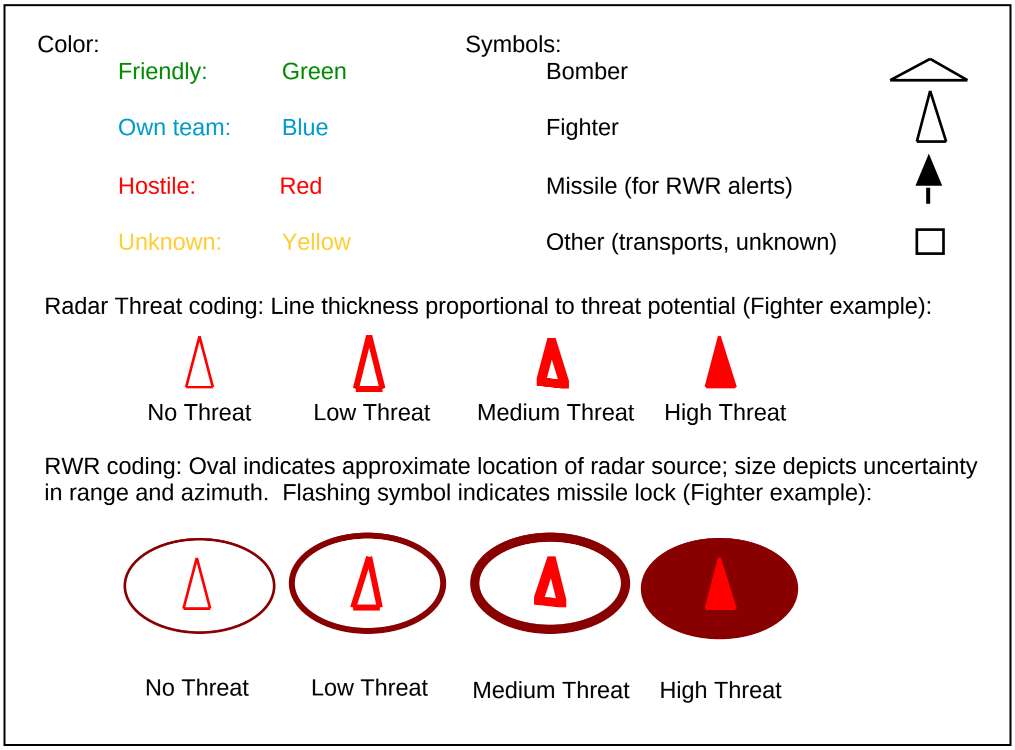


Figure 9. Air-to-Air Radar Symbology.

When the RWR detects a radar source, an oval is superimposed on the display to indicate the source's estimated origin. The lower part of the figure shows the RWR oval superimposed on a radar icon. Again, line thickness is proportional to the estimated threat potential. The size of the oval in a direction parallel to the radar line-of-sight indicates uncertainty in range, while the size in the direction perpendicular to the line-of-sight (in the horizontal plane) indicates the uncertainty in azimuth. When the RWR detects a missile lock, the icon will flash, to draw attention to the expected origin of the incoming missile. In the event that the RWR detects a radar signal at a distance beyond the current radar range setting, an arrow appears at the boundary of the radar display to indicate the direction of the incoming radar signal. The arrow's thickness is proportional to the estimated threat potential.

For level 3 aiding, we have incorporated the following audio alerts into our prototype:

- An audio warning tone that sounds when the RWR detects a hostile radar signal at a range beyond the current radar display setting
- An audio alert tone that sounds when the RWR detects an enemy missile lock on ownship

Both audio alerts are correlated with visual icons that indicate the same information. Experimental research has shown that correlated bi-modal alerting provides improved response latencies and enhanced subjective SA over uni-modal alerting (Selcon, Taylor, & Shadrake, 1992). These alerts could be made localized using 3-D audio, so that the origin of the sound corresponds to the direction of the detected threat. There at least two potential modes of operation for such alerting: 1) bi-modal alerts are presented in all cases; or 2) bi-modal alerts are presented only when pilot workload increases beyond a certain threshold and/or the density of information on the radar beyond a certain level.

For level 4 aiding, the OLIPSA prototype can automatically select appropriate radar display range, in the event that an enemy radar at or above a given threat threshold is detected at a range beyond the current display setting. Again, this automation can happen whenever the tactical situation and system configuration warrants it, or when the pilot workload rises beyond a certain threshold. Finally, for level 5 adaptation, our prototype system can automatically release countermeasures to confuse threat missile sensors in the course of a missile evasion maneuver.

Figure 10 presents a snapshot of our integrated display during a simulation. The italicized annotations show the meaning of the various symbology elements. At the instant shown, an incoming missile is approximately 7.5 nautical miles away from ownship, while the aircraft that fired it is veering to its left. At the same time, the RWR has detected a medium threat fighter radar (as indicated by the "F" within the arrow) at a range greater than 20 nm (the current radar display setting).

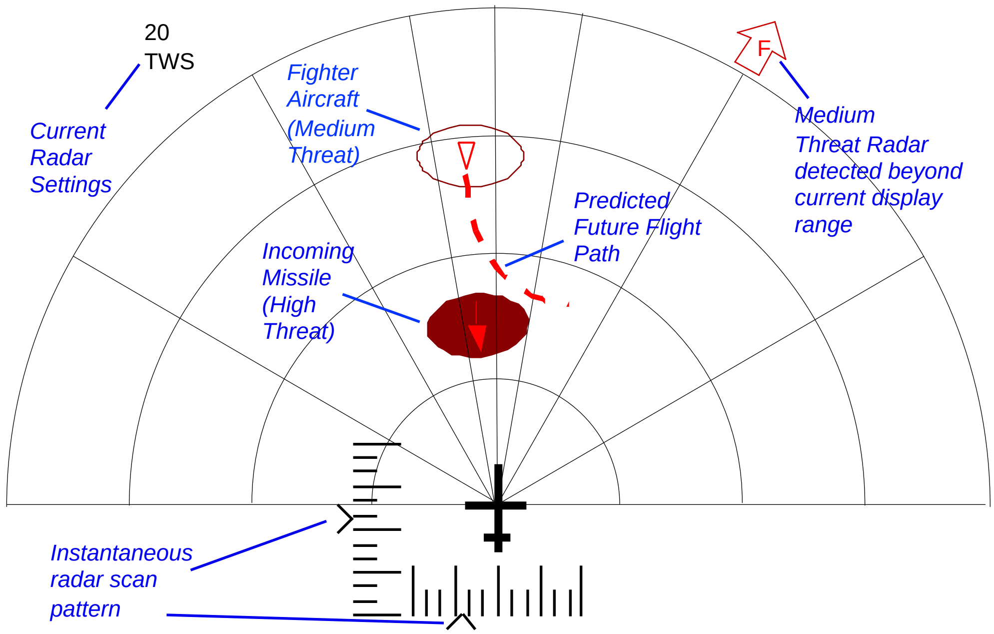


Figure 10. Prototype Radar Display.

CONCLUSIONS

This study has demonstrated the basic feasibility of a concept prototype for on-line situation assessment. OLIPSA uses belief networks and fuzzy logic for a robust, extensible framework for current situation assessment modeling. Belief networks readily facilitate extending existing models with new variables or dependencies without re-coding. This offers a considerable benefit over conventional expert system approaches of domain knowledge modeling, in which it is necessary to redesign rulebases whenever a new variable is introduced. The use of fuzzy logic provides an SA module that generates smooth outputs for smooth inputs. Case-based reasoning provides a practical means of implementing experience-based outcome prediction.

The OLIPSA prototype shows how an on-line SA processor can be used for diverse in-cockpit functions such as display content generation, multi-modal alerting, sensor management, and task automation. Each of these functions was demonstrated on a prototype air-to-air radar display. OLIPSA provides a set of conceptual building blocks for follow-on development, which we are now using to develop situation assessment models for uninhabited combat air vehicle (UCAV) operations.

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