Human Centered Decision Support for Anti-Air Warfare on Naval Platforms

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SUMMARY

In anti-air warfare (AAW), rapidly evolving situations require very fast decisions which are extremely difficult to make, especially in so-called "mixed environments" where neutral, friendly, and hostile objects are present. Thus the importance of supporting AAW decision makers increases significantly. The basis of any support system must be an ergonomically designed user interface covering all stages of human information processing. Additionally, improving the cognitive processes of operators by computer-based decision proposals is important. To achieve this, techniques beyond rule-based "artificial intelligence" (AI) are considered, such as Bayesian belief networks, case-based reasoning, and fuzzy theory. To be able to operate advanced AI methods fruitfully, it is necessary to acquire, describe, formalize, and represent knowledge and problem solving strategies of domain experts. The first step is the identification of decision making variables by means of an empirical knowledge acquisition. Military experts will be observed when making decisions and asked to substantiate them while facing simulated scenarios. The knowledge acquired this way is needed for case bases, which intelligent agents can access, as well as for an analysis of operators' information demands.

1.0 INTRODUCTION

As the scope of military duties shifts more and more from pure national defense towards participating in multinational peace-keeping missions, future command and control (C^2) systems have to meet the specific requirements of such "out of area" missions, which are characterized by eminently high complexity and uncertainty in the tasks of situation recognition and assessment, as well as in the choice of adequate measures. The presence of neutral, friendly, and hostile objects necessitates non-ambiguous identification. Thereby, the identification of unknown objects, the detection of the abilities and intentions of possibly threatening objects, the interpretation of rules of engagement, as well as the ultimate decision on whether or not to engage a particular object lead to exceedingly difficult decision making situations.

Besides these new types of missions there is also a lot of technological advancement. Range, speed, and accuracy of weapons increase, and so do sensors and communication facilities. The amount of available data about the operational area has noticeably expanded, e.g., by satellites and AWACS. Figure 1 shows an overview of some factors relevant to tactical decision making onboard naval vessels. To emphasize the increasing importance of communications, computers, intelligence, surveillance, and reconnaissance in C^2 the term C^4ISR has arisen.

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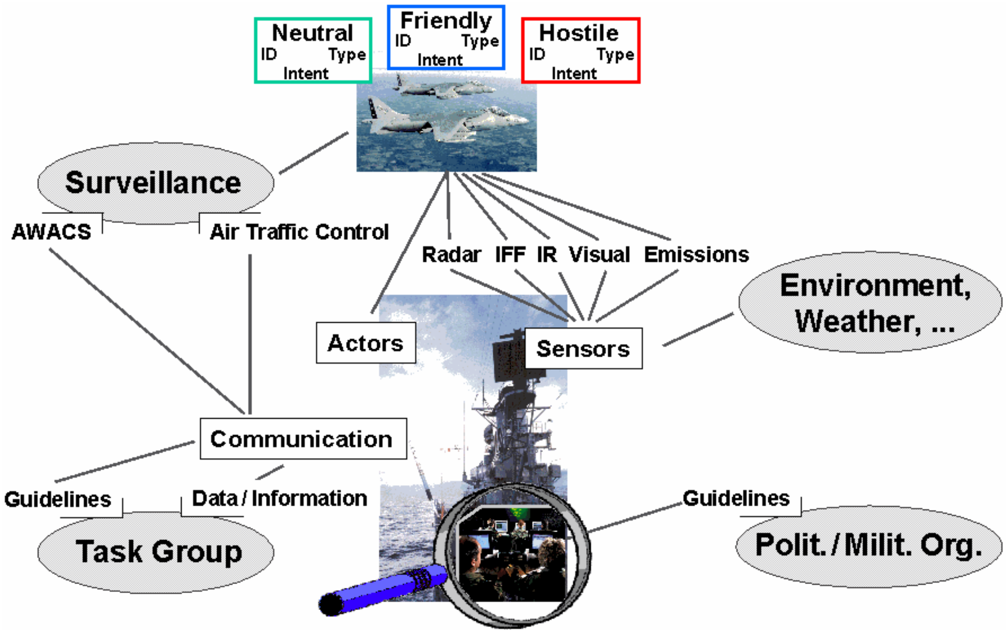


Figure 1: Overview of the Problem Space [Boller 2001].

Consequently human decision makers are confronted with an increasing amount of information but have less time remaining to ponder. Especially the rapidly changing situations in the AAW domain demand decisions be made and, if considered necessary, actions be taken extremely fast. This means high workload and stress for the human decision makers and will possibly result in wrong decisions with serious consequences. Thus the importance of supporting decision makers to reduce workload and therewith improve planning, decision making, and operation safety increases significantly.

2.0 GUIDELINES FOR BUILDING AN ADAPTIVE SUPPORT SYSTEM

The basis of any support system must be an ergonomically optimized user interface that features task- and user-adapted handling and supports all stages of human information processing. Wickens' model of multiple resources [Wickens 1991] implies that humans possess different resources for the various successive stages of information processing:

- Perception,
- Cognition, and
- Sensorimotor reaction.

Therefore, a goal of the design of a user interface must be to reach an equable exploitation of the resources being available for these different stages. In complex man-machine systems the necessity to optimally exploit the operator's resources creates demand for software-based support of all mentioned stages of information processing. This can be attained by a knowledge-based assistant system inserted between the visualization part of the user interface and the technical system as shown in Figure 2.

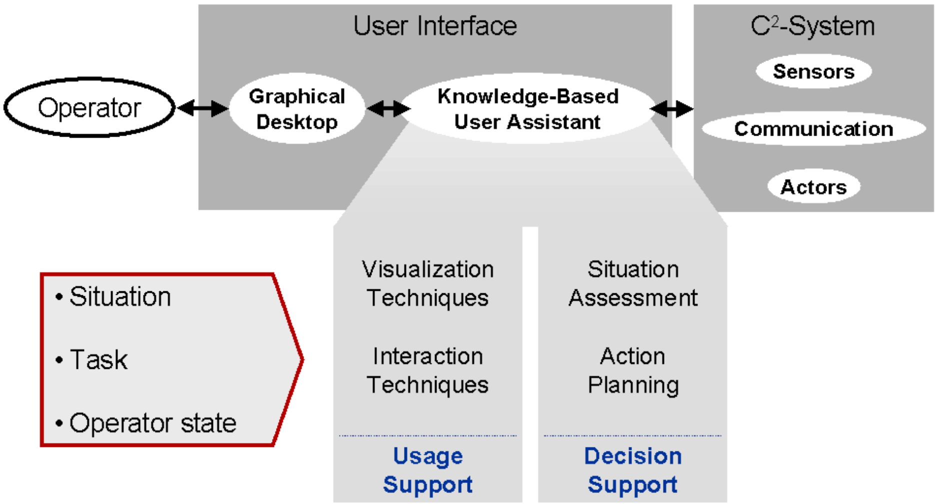


Figure 2: Starting Points for Adaptive User Support.

First, the concept for a knowledge-based support system must provide a component to support C^2 system usage. The modules integrated herein shall support all stages of information collection, processing, and transformation in a way so that operators can interact with the system intuitively and reach an adequate situational awareness.

Second, besides an improved design of the man-machine dialog, supporting the cognitive processes of operators by computer-based means becomes ever more important. Hence the authors' support concept is primarily intended to provide agents that derive situation assessment proposals based on the available information. Thereby the situation assessment module is to influence all other modules to achieve an adequate support for each task in any situation. The assistance system shall not replace the operator but rather serve as a cognitive amplifier.

Table 1: Scale of Degrees of Automation [Sheridan 1992]

Degree of Automation	System Features
1	The computer offers no assistance, human must do it all.
2	The computer offers a complete set of action alternatives, and
3	narrows the selection down to a few, or
4	suggests one, and
5	executes that suggestion if the human approves, or
6	allows the human a restricted time to veto before automatic execution, or
7	executes automatically, then necessarily informs the human, or
8	informs him after execution only if he asks, or
9	informs him after execution if it, the computer, decides to.
10	The computer decides everything and acts autonomously, ignoring the human.

Sheridan [Sheridan 1992] differentiates ten degrees of automation, as shown in Table 1. Level 1 would mean not to provide any decision support at all. Levels 8-10 are not eligible for tactical decision making because in these approaches operators are completely dismissed from the loop. Level 7 can be regarded acceptable only for the initiation of so-called “last-chance” defenses against very critical threats, such as an inbound anti-ship missile. The support provided to operators should normally reside among levels 2 to 6 and adapt according to the complexity of the task at hand, the over all situation, and the operator state, as far as it is possible to assess it.

3.0 ASPECTS OF HUMAN DECISION MAKING

3.1 The Impact of Information on Performance

The following primitives have been identified by Alberts et al. [Alberts 2001] as being needed to investigate how information affects performance:

- Sensing: direct sensing happens with humans’ senses (e.g., seeing). Visual recognition of an air track is an example for direct sensing from the treated domain. However, most identification relies on indirect sensing, such as radio detection and ranging (radar).
- Data: data are the raw form of what has been received by any sensing device.
- Information: the result of merging individual pieces of data into meaningful context. Some observations can be lost, due to filtering by perceptual lenses.
- Knowledge: the available information inspires patterns from which conclusions are drawn. Knowledge about the situation results from these conclusions. This procedure is influenced by knowledge resulting from training, experience, and interaction with other humans.
- Awareness: the result of combining prior knowledge, beliefs, and current perceptions related to the situation. It is unique to any individual; nevertheless, military training aims at obtaining a common awareness.
- Understanding: sufficient awareness and knowledge to assess possible future patterns and consequences of the situation constitute understanding. It focuses on what the situation can become as well as on the impact of making different decisions.
- Decisions: the choices about what to do. Some decisions imply actions to fulfill. Decisions should be based on understanding; however, they can of course also be made without understanding, which is undoubtedly the case to be avoided.
- Actions: some decisions being made trigger actions to be executed.

Because this paper concentrates exclusively on single operator tasks in AAW, sharing, collaboration, and synchronization have been skipped.

3.2 Threat Evaluation on the Basis of Observed Activities

The following definitions are required to model AAW decision making processes:

- Activities: the behavior of the track that is actually observable, for instance its suitability to an airway, its maneuvers, or weapon releases.
- Options: all activities the track is able to perform in the near future referring to its current situation.
- Intention: the long term mission goal of the aircraft’s pilot. The AAW-operator, taking into consideration the activities observed up to the present, can merely guess which of the imaginable intentions is most probable and which of its options the track is therefore most likely to realize.
- Threat: depending on the detected intention, in a threat evaluation the likelihood of an attack on own forces among other things is analyzed. The result can lead to an engagement.

Figure 3 shows an example of how options, likeliest intentions, and threat assessment evolve over time with developing activities of a track.

Activities	Options	Likeliest intentions	Threat assessment
Flying in accordance with airway	•Fly i.a.w. airway •Change altitude •Change speed •Change course	•Air transport •Could be any •Could be any •Could be any	•No threat •No threat (yet) •No threat (yet) •No threat (yet)
Changing course	•Depart from ownship •Approach ownship •Fly inbound maneuver	•Air transport •Rec. / Harass. / Attack •Rec. / Harass. / Attack	•No threat •Looming threat •Looming threat
Flying inbound maneuver	•Reconnoiter ownship •Harass ownship •Release weapon	•Reconnaissance •Harassment •Attack	•Acute threat •Acute threat •Acute threat
Releasing weapon	•Attack ownship again •Escape from ownship	•Attack •Attack	•Critical threat •Critical threat

Time

Figure 3: From Activities to Threat Evaluation, a Refinement following Döring et al [Döring 2002].

3.3 The Three Levels of Decision Making Performance

As shown in Figure 4, decision making can be divided into the steps “situation assessment” and “solution generation” [Dörfel 1999]. According to Rasmussen [Rasmussen 1983], information processing, as indicated by the cognitive level on which a decision is made, can be assigned to:

- Skill-based behavior: predetermined signals are recognized and interrelated directly with one or more actions to be performed.
- Rule-based behavior: situations are interpreted according to rules. Therefore, knowledge is extracted from the situation. Actions are triggered depending on the ascertained situation. The action planning results from the existing system knowledge that determines the manner of potential actions.
- Knowledge-based behavior: if there are no rules present for a situation, it thus represents a totally new experience, it is tried to assess the situation by calling in experiences from the past. Structuring on this and having regard to overall mission objectives a goal is defined and goal-directed action plans are formulated.

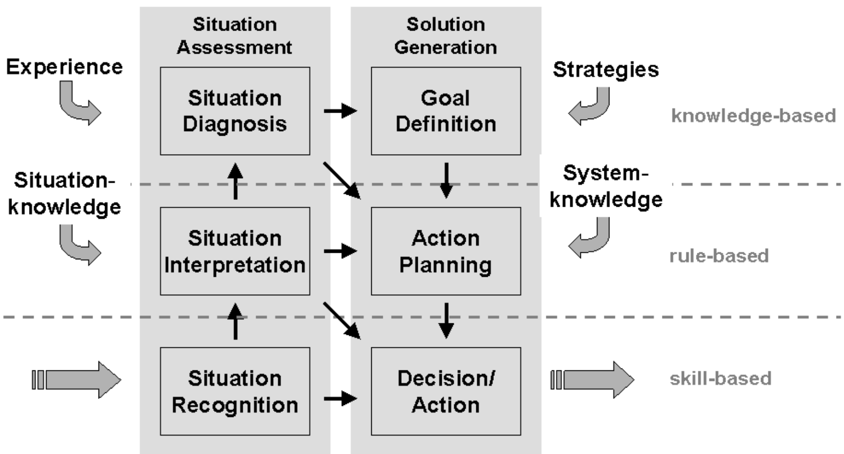


Figure 4: The Three Levels of Performance [Dörfel 1999].

By utilizing computer-based decision support systems it can be tried to emulate the corresponding human decision making processes closely matching.

4.0 VISUALIZATION ASPECTS

As pointed out in the introduction as well as in Figure 1, AAW operators onboard naval vessels have to make decisions based on a multitude of data and information. In current C^2 systems these are predominantly presented in alphanumeric form. According to Card [Card 1999] a user-centered presentation of complex data should feature the use of computer-supported, interactive, visual representations to amplify cognition by:

- increasing the memory and processing resources available to operators,
- reducing the search for information,
- using visual representations to enhance the detection of patterns,
- enabling perceptual inference operations,
- using perceptual attention mechanisms for monitoring, and
- encoding information in a manipulable medium.

Some inferences can be drawn easily due to graphical visualization, whereas without it would be more difficult. By appropriately mapping information into visual form cognitive effort can be enhanced. The over all idea is to support thinking by visual perception.

Figure 5 shows two states of a safety parameter monitoring display [Wickens 1997] designed to support nuclear power plant operators. A polygon connects the values, indicated by the distance from the center, of eight parameters. As long as everything is all right a harmonic uniform polygon, as the one on the left, originates from the data. The right one indicates that there are parameters that deviate from normal. Similar visualization techniques can be developed to support the information collection, processing, and transformation phases of AAW operators [Pfendler 1999]. Finding an adequate way to provide them with all relevant information is an essential with the development of future C^2 systems.

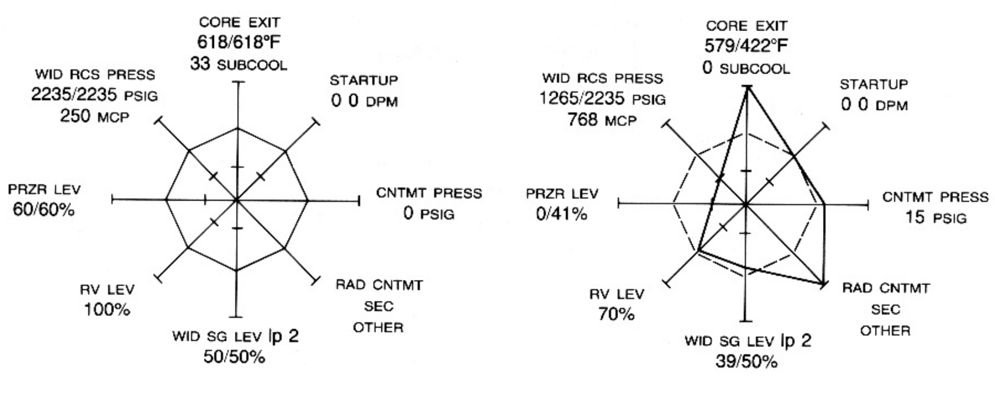


Figure 5: Integrated Polar Display for Nuclear Power [Wickens 1997], the right one indicates Parameter Deviations.

5.0 FORMAL DECISION SUPPORT TECHNIQUES

The main goal of the aspired support system is to draw conclusions from the data on hand regarding all accumulated knowledge. To achieve a sufficient quality of reasoning from an automatic system, mathematically consistent inference techniques are needed. Many currently realized computerized support systems try to fully describe all anticipated situations as rules. Such rules act upon Boolean logic and deduce or exclude solutions assuredly. There cannot be anything in-between at all.

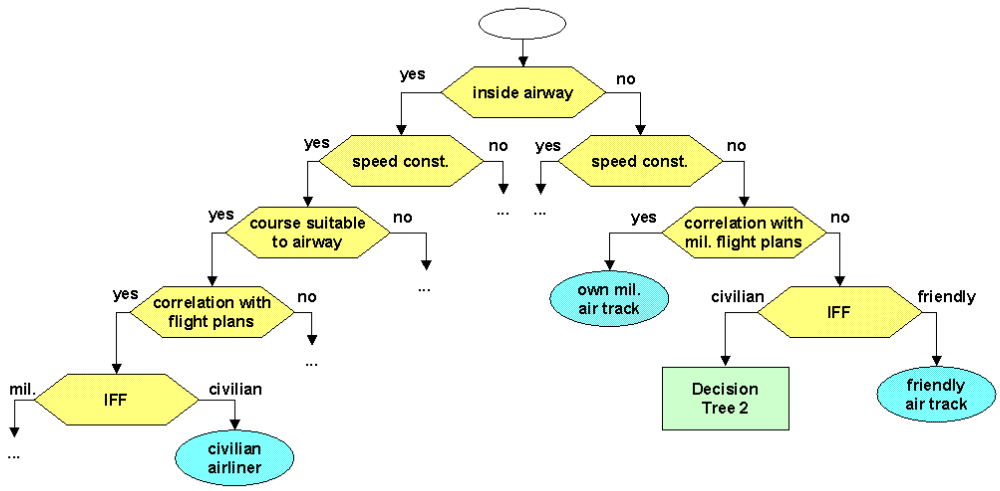
In contrast, military situations can often be characterized by one or more of the following aspects:

- They cannot be described on the basis of univocal rules. These kind of situations can only be described and solved by calling in previously acquired know-how.
- They are not conform to any expectations that have been considered within the system development process and are not accounted for in the system concept therefore.
- Because of physical and especially tactical restrictions with the use of sensors a complete and up to date set of data does not necessarily exist for all objects in the operational environment.
- They allow several inconsistent interpretations. In the AAW domain this can arise, for instance, from the fact that in terms of speed, course, and altitude an enemy warplane can behave similarly to a neutral cargo plane.

According to the introduced levels of decision making performance, a purely rule-based support system is not capable of supporting the human decision maker in a situation in which knowledge-based acting is essential. Therefore, approaches beyond rule-based knowledge representation have to be taken into account.

5.1 Description of Techniques

5.1.1 Boolean Inference



	inside airway	speed const.	course suitable to airway	correlation with flight plans	IFF
civilian airliner	yes	yes	yes	yes	civilian
own mil. air track	no	no		yes	
friendly air track	no	no		no	friendly
Decision Tree 2	no	no		no	civilian

Figure 6: Example Decision Tree and -Table.

The previous elucidation has made clear that in military environments there are situations that purely rule-based systems cannot appropriately deal with. Nevertheless, constellations in which no other support technique can outperform Boolean inference do exist as well. For instance, no airliner will ever have a turn rate of more than about 1 degree per second. Not only that it could not be expected of the passengers, in fact big planes, which are usually deployed for passenger transportation, are not even capable of performing such a rate. Therefore, if a particularly high turn rate is observed, the hypothesis that the track could be non-military can be excluded.

There are two variants for the implementation of such rules: decision trees and -tables (Figure 6). Decision trees consist of inner knots that contain questions, edges meaning answer alternatives, and leaves that can be solutions or invocations of other decision trees. A tree is processed by alternately asking a question and marking out a solution or the next question by applying the associated rules. Trees are capable of representing knowledge in a quite compressed manner. Complex decision trees are difficult to alter due to the inherent dependencies. In contrast, decision tables represent rules independently and therewith allow very modular structuring. Because of this modularity, it might be necessary to implement complex preconditions as well as logical nesting.

5.1.2 Fuzzy Sets

In contrast to decision tables with sets of Boolean rules, fuzzy logic [Seising 1999] can be applied to tasks in which the degree of conformance can neither be set assuredly "true" nor "false" but merely be mapped to fuzzy sets. Such "fuzzy classifiers" are based on normative membership functions related to the object attributes to be classified (Figure 7).

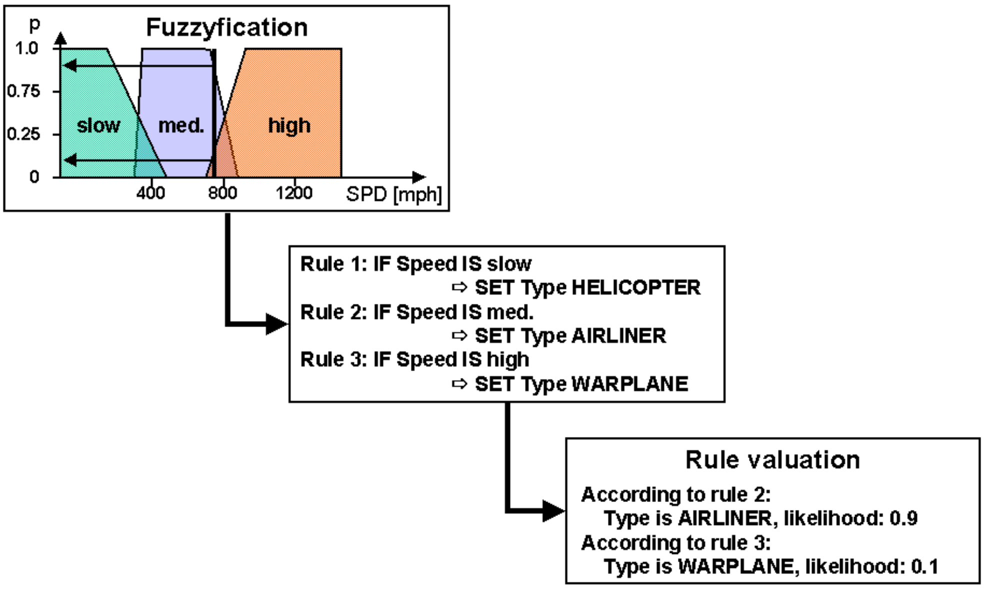


Figure 7: An Exemplary Fuzzy Classifier.

Throughout the fuzzification, the probability for an object attribute of belonging to a certain valuation class, e.g., *helicopter / airliner / warplane* or *suitable to airway / not suitable to airway* is stated. All discrete classifiers can be stochastically combined, for instance, using Bayesian belief networks, which are described beneath. Therewith likelihood ratios about the type of an object and the threat emanated from it can be deduced. The membership functions of classic fuzzy classifiers are static, whereas neuro-fuzzy techniques are capable of readjusting classifiers by modulating the applied membership functions.

5.1.3 Bayesian Belief Networks

The basic idea of Bayesian belief networks [Mitchell 1997] is very similar to heuristic classification with the difference that relationships between attributes and solutions are not estimated by experts but rather extracted from case databases. This form of statistical classification is suitable for problems for which a substantial, representative collection of successfully solved cases is available. Its most important advantage is that it provides the objectifiability of knowledge. The following requirements have to be fulfilled:

- Alternating Markovian independence of attributes
- Completeness of the set of solutions
- Alternating exclusion of solutions
- Representativeness of the case collection
- Availability of a sufficient set of cases for any alternative solution

The theorem of Bayes requires the a priori probability of any solution and the conditional probability of any attribute. Both kinds of probabilities can be calculated from a case collection. Computerized procedures to model networks based on case collections are available as well.

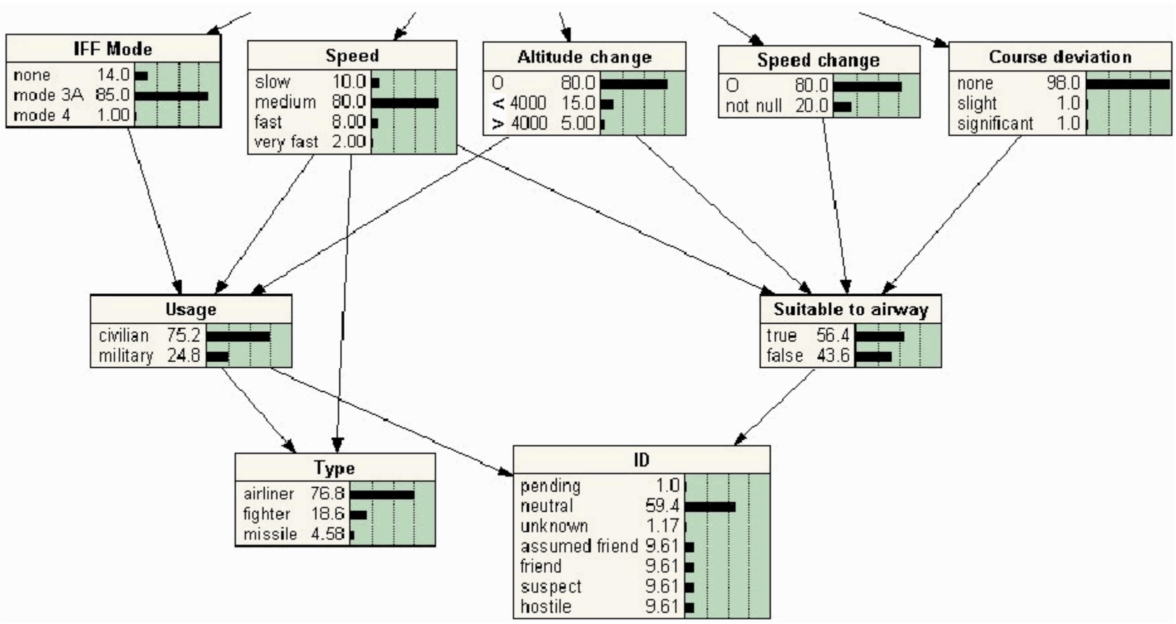


Figure 8: An Exemplary Trained Bayesian Belief Network.

Figure 8 shows an exemplary Bayesian belief network for the AAW domain. The knots show the conditional probabilities of occurrence for any parameter value of an attribute, given all of its predecessors. The omitted knots at the top, indicated by the arrows, stand for a yet unknown number of preconditions that influence the likelihood distributions of the other variables, such as the political situation, the surrounding landscape, or the weather.

5.1.4 Case-Based Reasoning

Instance-based methods, such as case-based reasoning [Puppe 1996] are so-called lazy learning methods, because they do not generalize beyond their accumulated data unless a new classification problem emerges. Once a new case occurs, similar instances are analyzed. If the nearest found case is similar enough, subject to the condition that there is no comparable case with an entirely different solution to the new one, its solution is taken over. Thereby the respectively corresponding characteristics of cases are compared, and a similarity index is calculated out of the individual comparisons. Case-based classification is eligible for classification problems for which enfolded collections of real or made up cases with correct solutions and detailed logging of all attributes exist.

In principle the case on hand must be compared to every known case in the database to find out which one is the most similar. A means to reduce this effort is to assemble very similar cases to clusters that are represented by joint agents. Furthermore, pre-selection strategies could be advantageous, e.g., pre-selection on the basis of particularly important attributes and hill-climbing via case neighborhood, whereat closest neighbors are checked until the utterly most similar one has been found.

5.1.5 Artificial Neural Networks

Artificial neural networks (ANN) [Schöneburg 1990] simulate the way biological nervous systems are believed to work. Namely the human brain structurally consists of neurons. ANN are based on simulated neurons which are joined to networks in many different ways. These networks are able to create relationships among data and generalize from stored examples to new cases. Thus they have the capability to acquire knowledge by learning from prior experiences, similar to adaptive biological learning. Furthermore ANN can deal with imprecise, probabilistic, and fuzzy data. For the time being, typical fields of application include the recognition of speech, characters, and signals.

In contrast to conventional algorithmic approaches, in which inference is performed by pre-determined steps and data are stored at specific locations, neural networks use highly distributed representations and transformations that operate collaterally. The inherent high grade of parallel processing has led to the construction of special parallel processing hardware to facilitate the implementation of particularly efficient ANN. Unfortunately neural networks cannot comprehensibly communicate the path leading to a particular solution nor even give any explanation at all.

5.1.6 Genetic Algorithms

The idea of genetic algorithms (GA) [Mitchell 1997] was inspired by Darwin's theory of evolution. In contrast to conventional expert systems that specialize or complexify given hypotheses referring exclusively to new cases and determined rules, GA simulate biological evolution by repeatedly mutating and recombining parts of the existing hypotheses. This is motivated by the hope that the modified ones will be better than the old ones. After each mutation, the new hypotheses are evaluated using some previously fixed fitness criteria. Thus GA are able to identify good hypotheses from spaces of candidates. So far they have been used successfully, for instance, to improve the topology of artificial neural networks, to learn rules for robot control, and for a number of optimization tasks.

5.2 Evaluation of Techniques

As soon as a situation in AAW becomes really delicate, human assessment is essential. But operators are capable of doing this job properly only if they can retain an adequate situational awareness despite being supported. Therefore, there has to be a sufficient amount of transparency with the applied support system. Evidence for this can also be found in the outcomes of an earlier study [Boller 2000] in which a prototypal rule-based support system was evaluated by Navy personnel. The test persons made complaints about being out of the loop. Whenever critical situations evolved they felt like being reduced to confirming automated application of rules by clicking, without having the chance to get an understanding of what was happening around them and of what they, respectively the support system, were doing.

Hence the applied techniques in the new support system must enable the operator to retain an adequate situational awareness. Certain knowledge-based techniques can provide auxiliary information about the way that led to their conclusions, others cannot. For this reason, neural networks are not considered a good strategy as they lack any transparency. Generic algorithms are also not appropriate due to their inherent mutation that makes them unpredictable.

6.0 THE EMPIRICAL APPROACH TO KNOWLEDGE ACQUISITION

In order to find out which events and attributes are relevant to object identification, intent recognition, and threat evaluation in AAW an empirical study with experienced operators will be undertaken. The goal is to acquire, describe, formalize, and represent practical expert knowledge. This is needed to frame a case-base, which is necessary to operate the aforementioned knowledge representation techniques. Additionally, the gained data shall be used for general task and information analyses to yield human centered design approaches for visualization and handling.

To act as experimentation facility and demonstrator a modular and extendible laboratory test bed has been developed. It consists of three parts: data generation, human-machine interface (HMI) for subject interaction, and experiment control.

The data generation is done with STAGE (Scenario Toolkit And Generation Environment), which is a commercial-off-the-shelf software used by numerous suppliers of military equipment. With STAGE simulated scenarios for military applications can be created graphically and run in real time, whereby quasi-realistic sensor data are provided. The scenarios for the experiments are created in close cooperation with a German Navy school. The experiments can only be expected to provide useful and enfolding information if all relevant points are included in the scenarios. Therefore, they must include situations (Figure 9) that typically appear in navies' future scope of duties, e.g.:

- Operations in coastline regions
- Presence of airways
- Mixed environments with friendly, hostile, and neutral forces
- Additional sensor data provided by AWACS
- Ambiguous parameters and behaviors
- Incomplete data

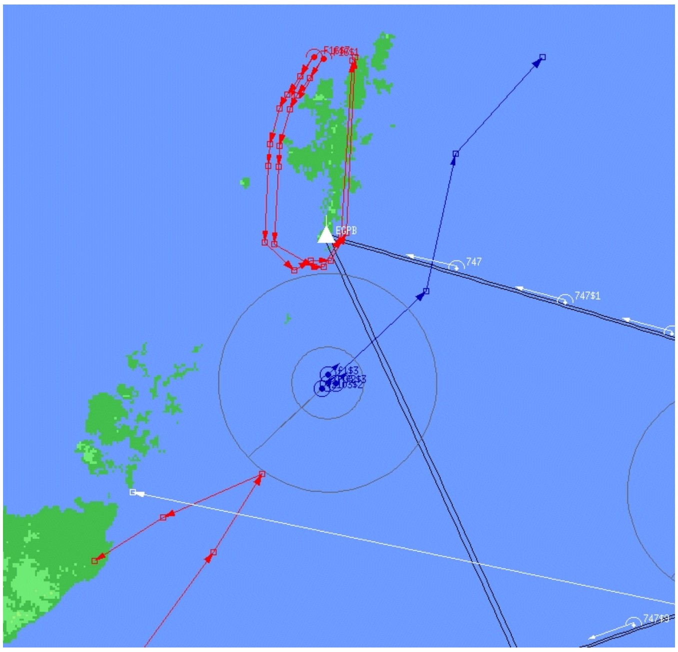


Figure 9: A Small Sample Scenario with Airways.

The HMI, which the subjects will face, is designed in the style of presently existing C^2 systems (Figure 10) to make its functionality and usability easy to learn for people who work with current systems. The presentation of information takes place in two display areas: plan position indicator (PPI) and track information display. A single object can be marked by clicking on its symbol within the PPI. Then all available sensor data belonging to that object are displayed in the track information area in an alphanumerical manner.

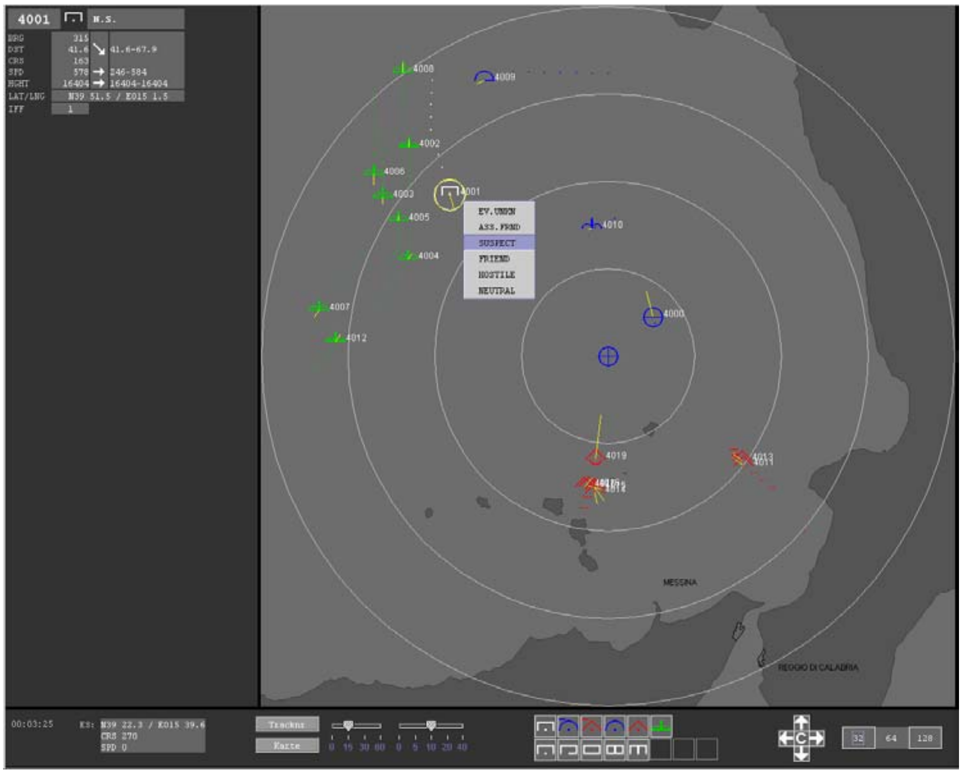


Figure 10: Graphical Desktop of the Laboratory Test Bed.

Other features of the HMI include:

- Buttons to set ID and type
- Buttons to scroll left, right, up, down, and to the center
- Hook function
- Zoomable range from 8 to 512 nautical miles
- Popup menus to set ID and type
- Optional map background
- Track numbers shown optionally
- Speed / direction vectors of adaptable length
- 0, 5, 10, 20, or 40 history points displayable for all tracks
- Selection, identification, and classification of multiple tracks at once
- Voice control

In the experiments the task of the military experts will be to make decisions while facing simulated scenarios. All events and parameter constellations as well as the whole user behavior are logged. That brings us to the third component of the test bed: the experiment control. Accompanying each decision the operators are requested to explain which of the object's attributes and behaviors contributed to their decision. Conceivable explanations include the following:

- Origin of track
- Course/speed changes
- IFF response
- Electronic emissions
- Rate of ascent / descent
- Suitability to airway pattern
- Flying in- / outbound
- Constellation / formation of multiple tracks

Human decision making is difficult to comprehend, therefore this list might lack some relevant points. To prevent the possible explanations from being limited to what the authors can think of at the time of experiment design, verbal annotation ("thinking aloud") of each decision is asked for, rather than filling in some kind of multiple choice questionnaire. In addition to the structured logging, which is to provide data that can be analyzed with algorithmic means, the complete screen activity is recorded with a screen recorder. In the experiments, a variant of this hardware that has been specially modified is deployed. This variant is capable of doing voice recording simultaneously to screen capture. This results in synchronous videos of the whole experiment, which can be reviewed by investigator and subject retrospectively to find out and supplement what has not been explained so far.

7.0 CONCLUSION AND OUTLOOK

The work human decision-makers onboard naval platforms have to perform is becoming more demanding due to new types of missions as well as advanced warplanes, more accurate weapons, and long-range sensors. Hence providing operators with adequate support is an essential requirement for future Navy C^2 systems. Because of the high complexity of most operator tasks full automation is not advisable. The final decisions must be made by human operators. Appropriately helping them to create a correct understanding of the situation can make the difference between a catastrophe and doing exactly the right thing.

Some particular behavior patterns can be modeled best by rule-based AI, for others more sophisticated approaches have to be considered. Five techniques have been described within this paper, whereof three shall be deemed to be potential constituents of the aspired support system. They all have in common that enfolding case-bases are needed to become able to apply them beneficially. A conceivable way to obtain such a case-base is empirical knowledge acquisition by means of a laboratory test bed. Furthermore, means to structure the so elicited knowledge have to be chosen and evaluated. Utilizing the methodology introduced here could yield helpful support for AAW operators, but yet there is much more research to be done.

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