# A Knowledge-Based Approach to Provide Adaptive Support for Anti-Air Warfare Decision Makers on Naval Vessels

**Dipl.-Wirt. Inform. Oliver Mooshage,**
**Dipl.-Ing. Helmut Distelmaier and Dipl.-Ing. Morten Grandt**
FGAN – Research Institute for Communication
Information Processing and Ergonomics
Ergonomics and Information Systems Department
Neuenahrer Strasse 20, 53343 Wachtberg
GERMANY

E-mail: mooshage@fgan.de / distelmaier@fgan.de / grandt@fgan.de

## *SUMMARY*

*Navies' future command and control ($C^2$) systems must particularly meet the specific requirements of multinational peace-keeping missions and littoral warfare, for the scope of military duties shifts towards such missions. Especially in the anti-air warfare (AAW) domain, rapidly changing situations demand decisions, which are extremely difficult to make in mixed environments, be made very fast. This means high mental workload for the human decision makers and will possibly result in wrong decisions with serious consequences. Thus the importance of supporting AAW decision makers to disencumber them increases significantly. An essential basis for such a support system is an ergonomically optimized, situation-, task-, and operator-adaptive interface that facilitates all aspects of human handling. Additionally, improving the cognitive processes of operators by computer based decision proposals becomes ever more important. Once knowledge and problem solving strategies of domain experts are described, formalized, and represented adequately, intelligent agents can be utilized to emulate human decision making processes relatively closely matching. Thereby it is important to bear in mind that a sufficient amount of transparency as to the agents' outcomes as well as overall situational awareness must be guaranteed, lest the operator be out of the loop. This paper introduces a methodology to support operators by the deployment of intelligent agents, as well as approaches concerning human/machine-interaction and the visualization of complex dynamic information. Moreover, the modular test bed is described, which has been created to demonstrate, evaluate, and elaborate the various innovations.*

## 1.0 CHARACTERISTICS OF THE PROBLEM AND THEIR IMPLICATIONS

The participation in so-called "out of area" missions, e.g., to back a peace keeping mission or to enforce an embargo, is characteristic for nowadays naval vessels' duties. In such missions, the tasks of situation recognition and assessment are characterized by eminently high complexity and uncertainty due to the simultaneous presence of neutral, friendly, and hostile objects. As opposed to the blue water scenarios of the cold war, the avoidance of collateral damage is mandatory now. Especially the rapidly changing situations in the AAW domain demand decisions be made and, if considered necessary, actions be taken extremely fast. Against this background 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 the shift in mission objectives there has also been a lot of technological advancement in recent years. Range, speed, and accuracy of weapons have increased, and so did sensors and communication facilities. The growing amount of available data about the operational area as well as the increasing importance of communication, computers, intelligence, surveillance, and reconnaissance in

*Paper presented at the RTO SCI Symposium on "Critical Design Issues for the Human-Machine Interface", held in Prague, Czech Republic, 19-21 May 2003, and published in RTO-MP-112.*

$C^2$ have given rise to the term $C^4$ISR. Figure 1 shows an overview of some factors relevant to tactical decision making onboard naval vessels.

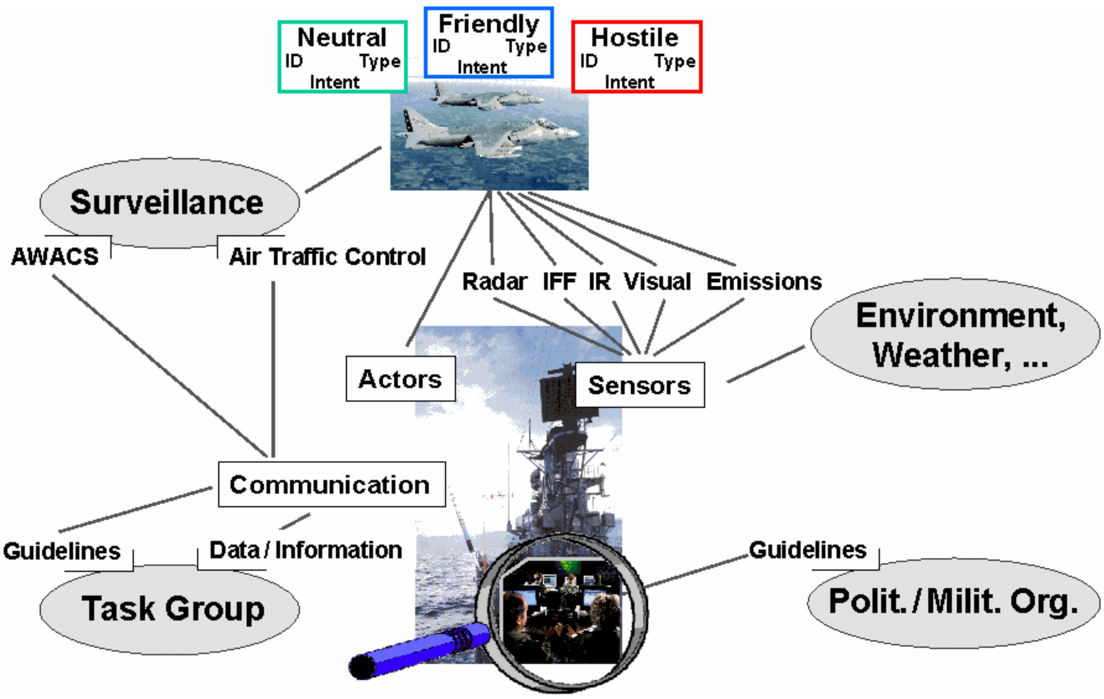


**Figure 1: Overview of the Problem Domain [Boller 2001].**

Consequently human decision makers have less time remaining to ponder. This means high workload and stress for them 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. The official report about the Vincennes incident [Fogarty 1988] concludes that stress, task fixation, and unconscious distortion of data may have played a major role in the inadvertent downing of an Iranian airliner. Inadequate displays, leading to mistaken beliefs, are likely to have contributed as well [Klein 1989]. The authors' concept envisions, besides an improved design of the man-machine dialog, supporting the cognitive processes of operators by computer-based means. Therefore it is intended to provide agents that derive situation assessment proposals based on the available information.

The following primitives, identified according to Alberts et al. [Alberts 2001], can be used to describe the processes involved in-between the observation of the surroundings and finally reacting to what is observed:

- 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.

The assistance system shall be deemed to be a cognitive amplifier, on no account shall human decision making be replaced by complete automation. AAW decision making, due to its immanent complexity and high stakes, must be considered as a naturalistic decision making process. Thus, all 8 characteristic factors, as mentioned by Orasanu & Connolly [Orasanu 1992], are at quite difficult levels:

- Ill-structured problems: Significant preparatory work is necessary to obtain an understanding of what is happening and what responses might be appropriate. There is no one best way to proceed.
- Uncertain dynamic environments: Because of environmental and weather conditions as well as restrictions with the use of sensors, data about nearby tracks may be scarce or ambiguous. Furthermore the settings are likely to change quickly, because air tracks move rather fast.
- Shifting, ill-defined, or competing goals: Decision makers are driven by multiple competing aims, such as self-protection and the avoidance of collateral damage (“engagement blue-on-green”). It is unclear how things should be traded off against each other.
- Action/feedback loops: Own actions taken can lead to reactions of other involved parties. By this means additional information can be generated, but new problems might occur, too. An object might feel provoked, for instance, when being targeted by illumination radar.
- Time stress: The existence of time pressure is obvious in AAW, because an air track is able to approach, and maybe launch a weapon, very quickly. Hence decision makers do not have much time to ponder and are likely to experience stress.
- High stakes: Outcomes of real significance to the participants are involved, such as being hit by enemy fire, mistakenly killing civilians, the loss of one’s career or even of one’s life.
- Multiple players: Although by definition the final decision is to the CO, there are several CIC team members involved in the decision making process, and the report of a single person can make the decisive difference.
- Organizational goals and norms: There are miscellaneous organizational settings relevant to the decision-making process. Therefore the applied goals and values cannot simply be the personal preferences. Furthermore, the organization may respond to the decision makers’ difficulties.

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 overall situation, and the operator state, as far as it is possible to assess it.

**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. |

This situation assessment module is to influence the behavior of the other modules with the objective of achieving an adequate support for each task in any situation. An important goal is to reach an equable exploitation of the resources being available for the different, successive stages of information processing, which are, according to Wickens' model of multiple resources [Wickens 1991]: perception, cognition, and sensorimotor reaction.

Figure 2 depicts the knowledge-based assistant system inserted between the visualization part of the user interface and the technical system as favored by the authors.

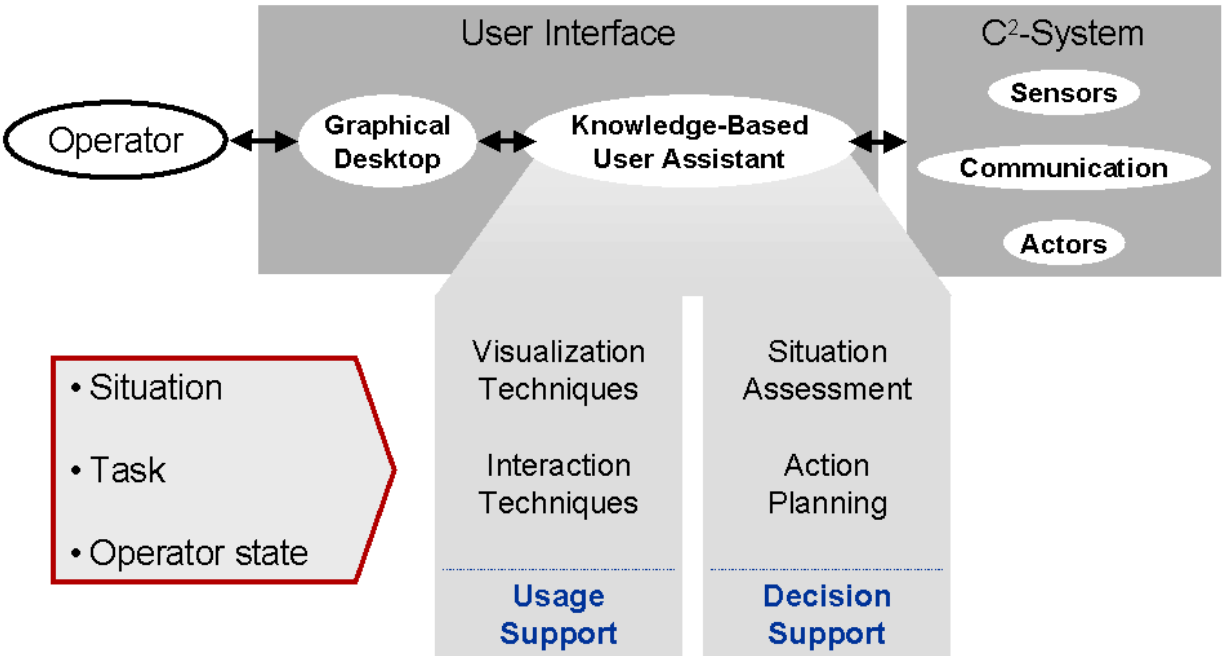


**Figure 2: Adaptive User Support by Means of Knowledge-Based User Assistance.**

# 2.0 THE MODULAR TEST BED FOR DEMONSTRATION AND EMPIRICAL TESTING

To act as demonstrator and experimentation facility a modular and extendible laboratory test bed has been developed. It consists of the following parts:

### Data Generation

The Scenario Toolkit And Generation Environment (STAGE), a commercial-off-the-shelf software used by numerous military research facilities and enterprises in the armaments industry, performs the generation of quasi-realistic sensor data. STAGE allows creating scenarios graphically and running them in real time as well as slow and fast motion. The scenarios used for experimentation and demonstration are created in close cooperation with experts from the Naval Operations School of the German Navy. As a matter of course scenarios must include situations 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, as well as incomplete data.

### Data Manager and SQL-Database

The database management module receives the generated data from the scenario generator and processes them for the subsequent user interaction and inference parts. Data are forwarded to the inference engine directly and stored in an SQL-database for the GUI module to retrieve from there, following the instant notification and whenever else needed.

### Graphical User Interface (GUI)

The GUI manager draws a screen that consists of two display areas and a bar with buttons. The presentation of information takes place in the plan position indicator (PPI) and track information displays. The design is meant to imitate the style of presently existing $C^2$ systems in order to make its functionality and usability comprehensible and easy to learn for people who work with current systems. A single object on the PPI can be selected by clicking on its symbol. Then all sensor data available for that object are displayed in the track information area in an alphanumerical manner. The selection process features the hook function, which means that it is possible to choose an object by clicking nearby rather than exactly upon. With a drag operation it is also possible to select multiple tracks at once. Marked objects can be assigned IDs and types using the corresponding buttons in the lower bar or with popup menus. Moreover the lower bar offers buttons to scroll the PPI in all directions, to change the zoom scale, as well as to toggle on/off showing track numbers, future position vectors of adaptable length, and a selectable quantity of history points on the PPI.

### Voice Control

The voice recognition module allows controlling several GUI functions by speech commands. By this means the assignment of IDs and types, scrolling around and zooming can be performed. Selecting single objects by saying their track number has been implemented as well, but shortly after turned out to be virtually impracticable. The effectiveness of speech commands at large in comparison with other input devices has been investigated in the experiment briefly described in the succeeding chapter.

### Map Server

The map server is intended to generate nautical charts for the surrounding area in all supported scales to be drawn in the background of the PPI optionally. Thereby it is possible to include specified ancillary information, to toggle between day and night representation, and to get terrain elevation information. The shape of landscape has an impact on the performance of sensors, which may be important to know for decision makers.

### Screen and Speech Recording

Any list of possible explanations for decisions made in simulated scenarios might lack relevant points, because human decision making is holistic and difficult to comprehend. To prevent the possible explanations from being limited to what the authors can think of at the time of designing an experiment, subjects will be asked to think aloud [Russo 1989] when making decisions, rather than to fill in some kind of multiple choice questionnaire. Therefore the complete screen activity can be captured with a specially modified screen recorder, which is capable of doing voice recording simultaneously. This makes possible taking synchronous videos of whole experiments, that can be reviewed by investigator and subject retrospectively to find out and supplement what has not been explained so far [Leplat 1981].

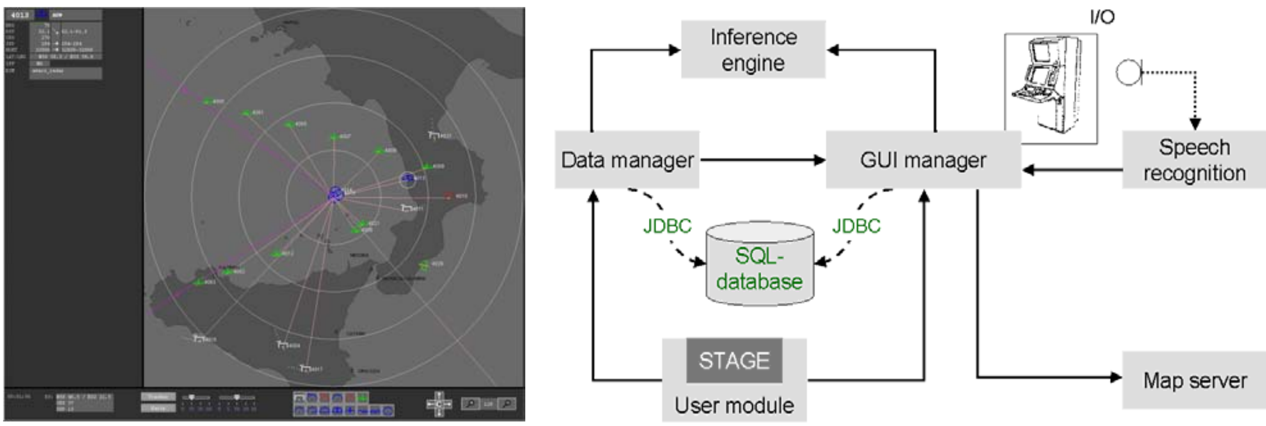


**Figure 3: Screenshot of the GUI Component on the Left, Topology of the Modular Test Bed on the Right.**

In experiments with military experts facing simulated scenarios it can be validated whether the developed decision making model, as presented beneath, really fits the human decision making process. Additionally, the gained data can be used for general task and information analyses to improve and enhance the human centered design approaches for visualization and handling.

## 3.0 AN INVESTIGATION WITH THE TEST BED CONCERNING INPUT DEVICES

As pointed out in the beginning, the authors' approach to disencumber naval decision makers focuses on three different facets: supporting operators by the deployment of intelligent agents, improving the visualization of complex dynamic information, and easing human/machine-interaction. The first experiment accomplished with the modular test bed concentrated on the last-mentioned aspect [Pfendler 2002]. The presumption is that the application of optimized input devices should reduce time demands for interaction by permitting operators a more intuitive and natural interaction. To confirm this a conventional computer mouse, two different roll balls as well as touch and speech input were compared in an empirical study. Furthermore, popup menus and conventional buttons were compared. For technical reasons (the touch input device was not sensitive enough at the bottom of the screen) the button bar was moved to the screen's upper edge. In addition to logging response times and failures, subjective workload was measured by the Two-Level Sequential Judgement Scale ZEIS [Pitrella 1988].

In a simplified AAW-task artificial sensor data were presented on the PPI. To reduce the amount of variables all scroll and zoom options were disabled. One track at a time appeared around the own ship, randomly placed on one of eight possible positions, and had to be identified and classified by the subjects as fast as possible. Then the next object appeared immediately after completion, totaling 32 objects per trial. In order to reduce training time for the naive subjects the task was simplified by reducing the number of possible IDs and types to only two each. The identities of the objects were indicated simply by their course, noticeable through the direction of the attached future position vector. Inbound tracks were defined as hostile objects, outbound tracks as friendly objects. For classification solely objects' speeds were used. Low speed, indicated by a short vector, meant a helicopter whereas high speed, indicated by a long vector, meant a fighter aircraft.

The results demonstrate that in general touch input and mouse show the fastest response times whereas speech input and the roll balls constitute the other extreme. As well, popup menus had significantly longer response times than the conventional buttons. The latter evidence can be explained by the additional operation of the right mouse button which is necessary to open the popup menu. With the exception of speech input, which was rated very low, workload was mostly consistent with the response times, but the strength of effects was smaller. There were no significant differences in number of response failures between all experimental conditions. Performance and workload measures document the advantages of conventional computer mouse and touch input. Compared to the computer mouse times for task completion with speech input and the roll balls were 40% higher. In comparison to touch input an increase of 60% was found. Absolutely the completion times increased from 3 to 5 seconds.

The results show that roll balls, which are often used with such tasks, are not the best solution. An argument often put forward in favor of them is that they are relatively robust against ship movements, as compared to mice only loosely connected by a cable. However, by taking adequate measures undesirable mouse displacements could be prevented. Furthermore, most people are trained with mice and are used to point at objects, the inherent motion when using a touch input, so that in contrast to the roll balls no additional training is necessary. Despite the low workload attributed to speech input, this method can be recommended not even for simple operations, because the time needed for verbal input, resulting from the duration of human vocalization as well as technical reasons, has found to be longer than with other interaction techniques. In addition, the demands on operators in respect to pronunciation are high if the phonetic model of the speech recognition system is not specifically accommodated to the vocabulary associated with a task.

This brief summary is meant to point up the possible fields of application for the modular test bed described in the preceding chapter. Interested readers can find detailed information about this experimentation in a forthcoming paper [Grandt 2003].

## 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 overall idea is to support thinking by visual perception.

Figure 4 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.

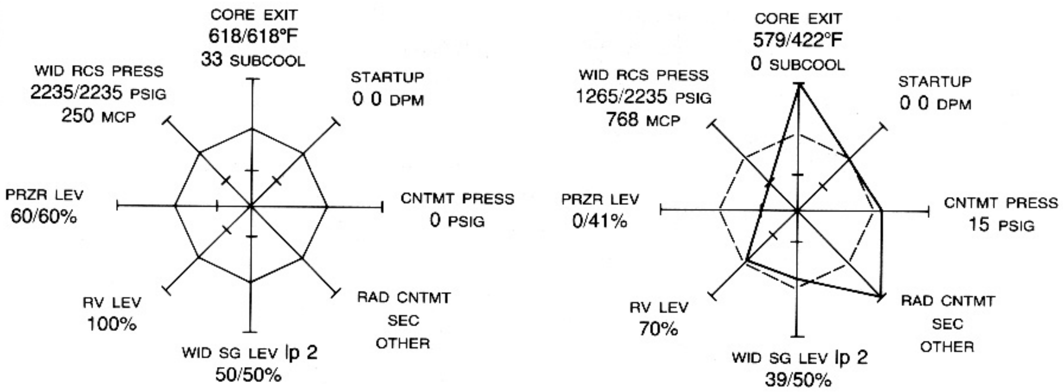


**Figure 4: Integrated Polar Display for Nuclear Power [Wickens 1997], the right one indicates parameter deviations.**

# 5.0 MEANS AND APPROACHES TO PROVIDE SUPPORT

## 5.1 Modeling Expert Knowledge and Implementing Rule-Based Support

Before a support system could be built the practical expert knowledge had to be acquired, described, formalized, and represented. In order to find out which events and attributes are relevant to object identification in AAW, interviews with several experts from the Naval Operations School of the German Navy took place. Additionally a lecture series about naval tactics was attended. Finally, a complete maneuver was observed onboard a German destroyer, whereby relevant crew members where asked to fill in an extensive questionnaire.

It appears functional to separate the collected rules on the basis of the involved objects as follows: Conclusions can be drawn due to a track

- On its own (e.g., maximum measured turn rate, frequency of course changes, emissions),
- In relation to static objects, such as civil airways (e.g., flying in accordance with airway, crossing airway), territories and zones (e.g., hostile origin, intrusion into restricted area), or military corridors (e.g., identification by correctly passing a transition corridor),
- In relation to the own ship resp. own task group (e.g., recognition of an inbound maneuver), and
- In relation to other dynamic objects (e.g., several air tracks flying in a military formation).

To achieve a convenient structuring, the Unified Modeling Language (UML) has been chosen. It has inherent similarities to semantic networks, the first approach to graphical knowledge structuring by Collins & Quillian [Collins 1969], such as the possibility to express *is a* and *has* relationships. UML's advantage is that its expressiveness is more comprehensive and that it has close ties to modern programming languages, such as Java. The UML diagrams in all, including the allocation of objects to the categories static and dynamic, are based upon the framework introduced by Döring et al. [Döring 2002].

Figure 5 shows an extract from the class diagram that comprises the model of the relevant decision making environment. Control Processes constitute the interfaces to data update processes and inquiries concerning most probable application and identity proposals. Track object subclasses model the entire environment. Ships and planes are dynamic track objects, whereas territories, airways, and corridors are regarded static track objects. Inference Processes are assigned to the subclasses as enumerated above. Collecting and conclusive inference processes prepare the findings to be presented to human operators. The shown extract does not include any lowest level classes, because their substantial amount would go far beyond the scope of this overview.

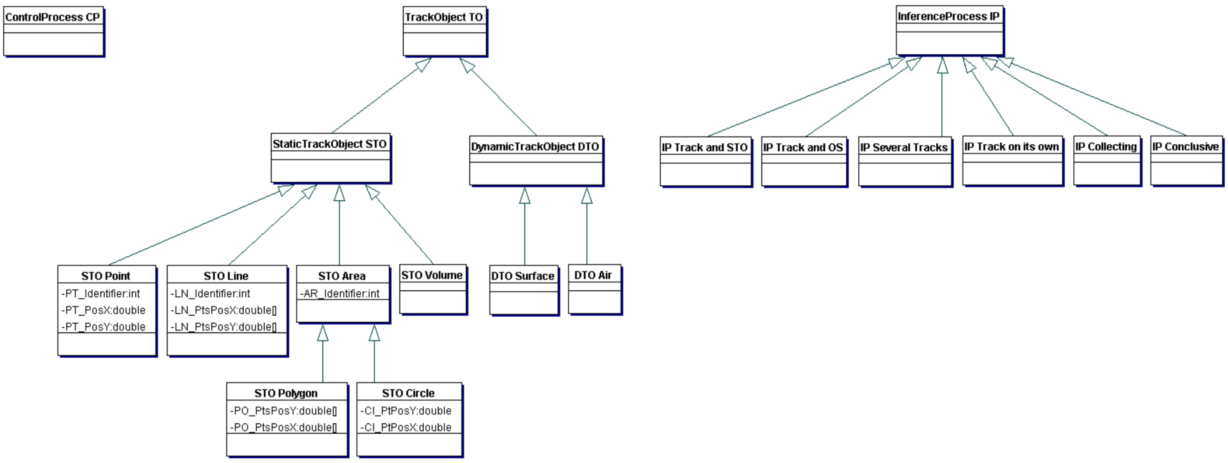


**Figure 5: The Upper Level Classes in the UML Class Diagram of the AAW Decision Making Environment.**

In the preceding chapters it has been made clear that in military environments there are situations that purely rule-based systems cannot appropriately deal with. Therefore the focus is on providing human decision makers with the best possible understanding rather than completely automating. Nevertheless, constellations in which no other technique can outperform Boolean inference do exist as well. For instance, no airliner will ever have a notedly high turn rate. 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. But humans cannot observe kinematic data of dozens of tracks at the same time, they cannot calculate all imaginable deductions within reasonable time, and of course on the long run they cannot remember every event that sometime caught their eyes. Beyond this, as soon as high stakes and time stress come into play, human decision makers tend to tunnel vision and the neglection of exclusion criteria.

As shown in Figure 6, human 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.

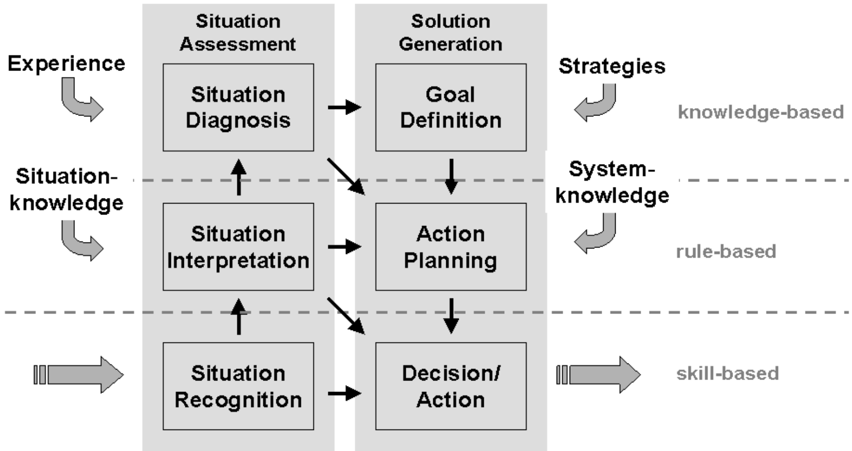


**Figure 6: The Three Levels of Performance [Dörfel 1999].**

Skill-based behavior means that no delay occurs besides response time, whereas with rule-based behavior it is necessary to adopt the appropriate rules. On the knowledge-based level, where the most demanding decisions are handled, surely the most time is needed for consideration. Of course human decision makers cannot be released from this responsibility by rule-based means, but decreasing the time needed for rule adoption makes available more time for the more challenging knowledge-based decision making processes.

The topology of the modular test bed, as shown in Figure 3, includes an inference engine that is completely rule-based at present. It receives the sensor data as they are generated and it has knowledge about the operational environment. Data are permanently observed and distinctive features are logged. Conclusions regarding application and identity are drawn, utilizing for inference the actual track data as well as all logged activities. A continuous automatic check will inform the operator when an ID proposal differs from the actual ID.

## 5.2 AI Techniques for Potential Future Enhancements

As has been said frequently before, making decisions in a military context means a lot more than can be dealt with completely using a rule-based approach. Therefore, for future enhancements, more sophisticated AI technologies must be taken into consideration, whereof the four most convenient ones are introduced in this chapter.

### Artificial Neural Networks

Artificial neural networks (ANN) [Schöneburg 1990] are very popular and wide spread within the AI research community. They 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. 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.

Because neural networks cannot comprehensibly communicate the path leading to a particular solution, designing support systems solely consisting of this technique would violate the well founded demand that operators must be enabled to retain an adequate situational awareness. For the time being, typical fields of ANN application include the recognition of speech, characters, and signals. For this reason they are particularly convenient for pattern recognition tasks, such as the detection of certain flight pattern. For instance, it is important to know when a track flies a reconnaissance maneuver, is refueled by another entity, or when multiple tracks fly in a military formation. It would at least be downright difficult, if not even impossible, to cover such events by algorithmic means.

**Fuzzy Sets**

Fuzzy theory [Seising 1999] is not really an AI technology on its own, yet constitutes a major enhancement to inference based on Boolean logic. The inference engine described in the above chapter acts upon Boolean logic and deduces or excludes solutions assuredly. That is to say there cannot be anything in-between at all. In contrast to such a set of *fulfilled* / *not fulfilled* type rules, fuzzy logic 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. Especially military situations frequently make for 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.

Throughout the fuzzification (Figure 7), 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. So-called “fuzzy classifiers” are based on normative membership functions related to the object attributes to be classified. All discrete classifiers can be stochastically combined, for instance, using Bayesian belief networks, which are described next. 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.

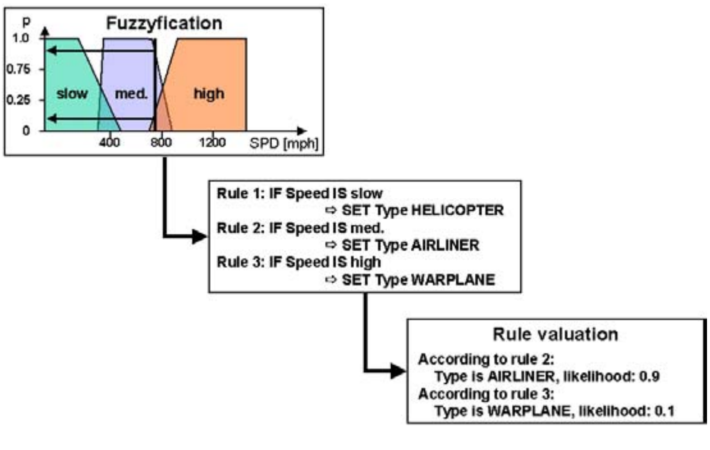


**Figure 7: An Exemplary Fuzzy Classifier.**

**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 need not be estimated by experts but can rather be extracted from case databases. The theorem of Bayes requires the a priori probability of any solution and the conditional probability of any attribute. Both kinds of probabilities can either be estimated by experts or calculated from case collections. For the latter method computerized procedures are available. To deploy a Bayesian belief network it behoves that the following preconditions 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

This form of statistical classification is suitable for problems for which a substantial, representative collection of successfully solved cases is available. This limitation makes it difficult to model a complete AAW decision making support system by this means, because critical and dangerous situations occur rather seldom but are undoubtedly especially important to deal with. However, the most outstanding advantage of Bayesian belief networks is that they provide objectifiability. For instance, certain radar units can be used on both friendly and hostile platforms. When a radar type has been identified and its distribution is known, an exact probability could be calculated automatically. But humans typically have difficulties with assessing conditional probabilities correctly and tend to neglect base rates, like has been illustrated by many examples, such as the blue and green taxis of Tversky & Kahneman [Tversky 1982]. Deficiencies of this type can be overcome using belief networks.

**Case-Based Reasoning**

Case-based reasoning [Puppe 1996], just like all instance-based techniques, is a so-called lazy learning method, which means that no generalization beyond the accumulated data takes place 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. 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.

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. It is likely to be a good alternative in respect of human tractability due to its apparent similarity to the recognition primed decision making model [Klein 1998]. But, contrary to the other AI technologies described in this chapter, which are regarded potential enhancements of the currently prosecuted rule-based approach, it would rather mean a replacement.

## 6.0 CONCLUSION AND OUTLOOK

Because of the new types of missions accompanied by more sophisticated actors and sensors the work human decision makers have to perform onboard naval vessels is becoming significantly more demanding. Hence providing operators with adequate support is an essential requirement for future Navy $C^2$ systems.

Full automation is not advisable as the most critical decision tasks feature eminently high complexity. Thus the final decisions must always be made by human operators. But disencumbering them and appropriately helping them to create a correct understanding of the situation can make the difference between a catastrophe and doing exactly the right thing. According to the authors' approach relief can be achieved by improving the visualization of complex dynamic information, easing human/machine-interaction, and the deployment of intelligent agents. It has been shown that some particular behavior patterns can be modeled by a rule-based inference engine, which would give human decision makers more time to deal with the more difficult knowledge-based decision making situations. In addition more AI technologies have been introduced briefly, which are eligible to enhance the rule-based module in the future.

## 7.0 REFERENCES

[Alberts 2001] D.S. Alberts, J.J. Garstka, R.E. Hayes, D.A. Signori, Understanding Information Age Warfare, Washington, DC: CCRP Publication Series, 2001.

[Boller 2001] H.E. Boller, "Grundlagen und Verfahren der Systemtechnik für Waffensysteme See", Lehrgang: Systemtechnik für Waffensysteme See, Mannheim: Bundesakademie für Wehrverwaltung und – technik, 2001.

[Card 1999] S.K. Card, J.D. Mackinlay, B. Shneiderman (Eds.), Readings in Information Visualization. Using Vision to Think, San Francisco: Morgan Kaufmann Publishers, 1999.

[Collins 1969] A.M. Collins, M.R. Quillian, "Retrieval Time from Semantic Memory", Journal of Verbal Learning and Verbal Behavior, 8, 1969, pp. 240-247.

[Dörfel 1999] G. Dörfel, H. Distelmaier, B. Döring, "Modeling Problem-Solving in Natural Settings", Command and Control Research and Technology Symposium, Vol. 1, Newport, RI: United States Naval War College, 1999, pp. 500-509.

[Döring 2002] B. Döring, G. Dörfel, H. Distelmaier, "Modelling Situational Awareness Information for Naval Decision Support Design", HFM Symposium on The Role of Humans in Intelligent and Automated Systems, Warsaw: NATO RTO, 2002.

[Fogarty 1988] W.M. Fogarty, Formal Investigation into the Circumstances Surrounding the Downing of a Commercial Airliner by the U.S.S. Vincennes (CG 49) on 3 July 1988. Unclassified Letter Ser. 1320 of 28 July 1988, to Commander in Chief, U.S. Central Command.

[Grandt 2003] M. Grandt, C. Pfendler, O. Mooshage, "Alternative Input Devices for Combat Direction Systems of Naval Ships", Forthcoming, 8th International Command and Control Research and Technology Symposium, Washington, DC: National Defense University, 2003.

[Klein 1989] G.A. Klein, "Do Decision Biases Explain Too Much?", Human Factors Society Bulletin, 32, 1989, 1-3.

[Klein 1998] G.A. Klein, Sources of Power: How People Make Decisions, Cambridge, MA: The MIT Press, 1998.

[Leplat 1981] J. Leplat, J.M. Hoc, "Subsequent Verbalization in the Study of Cognitive Processes", Ergonomics, 24, 1981, pp. 743-755.

[Mitchell 1997] T.M. Mitchell, Machine Learning, Boston: WCB/ McGraw-Hill, 1997.

[Orasanu 1993] J. Orasanu, T. Connolly, "The Reinvention of Decision Making" In: G.A. Klein, J. Orasanu, R. Calderwood, C.E. Zsambok (Eds.), Decision Making in Action: Models and Methods, pp. 3-20. Norwood, NJ: Ablex, 1993.

[Pfendler 1999] C. Pfendler, Zur Visualisierung dynamischer Information in Mensch-Maschine Schnittstellen, unpublished report, Wachtberg: FGAN e.V., 1999.

[Pfendler 2002] C. Pfendler, M. Grandt, G. Köhler, O. Mooshage, Vergleichende Bewertung von Eingabemedien für die Mensch-Maschine-Schnittstelle von FüWES der Marine, FKIE-Bericht Nr. 48, Wachtberg: FGAN e.V., 2002.

[Pitrella 1988] F.D. Pitrella, W.D. Käppler, Identification and Evaluation of Scale Design Principles in the Development of the Extended Range, Sequential Judgment Scale, Wachtberg: FGAN e.V., 1988.

[Puppe 1996] F. Puppe, U. Gappa, K. Poeck, S. Bamberger, Wissensbasierte Diagnose- und Informationssysteme. Mit Anwendungen des Expertensystem-Shell-Baukastens D3, Berlin: Springer, 1996.

[Rasmussen 1983] J. Rasmussen, "Skills, Rules and Knowledge; Signals, Signs and Symbols, and Other Distinctions in Human Performance Models", IEEE Transactions on Systems, Man and Cybernetics, Vol. SMC-13, 1983, pp. 257-266.

[Russo 1989] J.E. Russo, E.J. Johnson, D. Stephens, "The Validity of Verbal Protocols", Memory & Cognition, 17, 1989, pp. 759-769.

[Schöneburg 1990] E. Schöneburg, N. Hansen, A. Gawelczyk, Neuronale Neutzwerke : Einführung, Überblick und Anwendungsmöglichkeiten, Haar bei München: Markt-u.-Technik-Verl., 1990.

[Seising 1999] R. Seising, Fuzzy-Theorie und Stochastik: Modelle und Anwendungen in der Diskussion, Braunschweig: Vieweg, 1999.

[Sheridan 1992] T.B. Sheridan, Telerobotics, Automation, and Human Supervisory Control, Cambridge, MA: The MIT Press, 1992.

[Tversky 1982] A. Tversky, D. Kahneman, "Evidential Impact of Base Rates" In: D. Kahneman, P. Slovic, A. Tversky (Eds.), Judgment under Uncertainty: Heuristics and Biases, pp. 153-160. Cambridge: Cambridge University Press, 1982.

[Wickens 1991] C.D. Wickens, "Processing Resources and Attention" In: D.L. Damos (Ed.), Multiple-Task Performance, London: Taylor & Francis, 1991, pp. 3-34.

[Wickens 1997] C.D. Wickens, S.E. Gordon, Y. Liu, An Introduction to Human Factors Engineering, New York: Edison-Wesley Educational Publishers, 1997.