

UNCLASSIFIED

CENTRE LA SPEZIA
SACLANICEN-SM-176

14

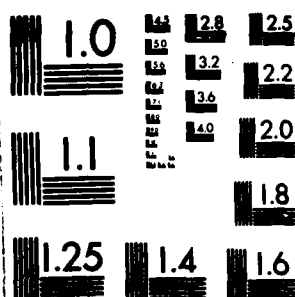
ML

END

DATE

FILED

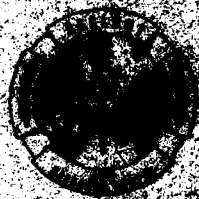
58



MICROCOPY RESOLUTION TEST CHART
NATIONAL BUREAU OF STANDARDS-1963-A

AD-A151 729

SACLANT ASW
RESEARCH CENTRE
MEXICO



The document is referred to a third party
in the interest of the public and the
following conditions:

1. The document shall be referred to a third party
in the interest of the public and the
following conditions:

2. The document shall be referred to a third party
in the interest of the public and the
following conditions:

18 December 1984

To : Distribution

Some copies of this document (SACLANTCEN SM-176) had already been distributed when it was found to contain some errors in its assembly. If you have already received a copy of SM-176 you are asked to destroy it and replace it by the attached, corrected copy.

Correct copies are identifiable by an asterisk (*) at the bottom of the distribution list.

STI

SACLANTCEN

SACLANTCEN MEMORANDUM SM-176

NORTH ATLANTIC TREATY ORGANIZATION

SACLANT ASW Research Centre
Viale San Bartolomeo 400,
I-19026 San Bartolomeo (SP), Italy.

tel: national 0187 540111
international + 39 187 540111
telex: 271148 SACENT I

ARTIFICIAL-INTELLIGENCE SYSTEMS
IN ANTISUBMARINE WARFARE:
RESULTS OF A PILOT STUDY WITH EXPERT SYSTEMS

by

Ingemar J. Cox
Lewis J. Lloyd

15 December 1984

This memorandum has been prepared within the SACLANTCEN
Systems Research Division as Part of Project 02.

T.G. Goldsberry
T.G. GOLDSBERRY
Division Chief



By	
Distribution/	
Availability/	
Dist	
Special	
A1	

TABLE OF CONTENTS

	<u>Page</u>
ABSTRACT	1
INTRODUCTION	1
1 EXPERT SYSTEMS	2
1.1 Background	2
1.2 Expert system frameworks	3
1.3 Limitations of expert systems	5
1.4 Future developments	8
2 APPLICATIONS IN ASW	9
2.1 Background	9
2.2 Previous military-sponsored research into artificial intelligence	9
2.3 Requirements for military expert systems	11
2.4 Near-future military applications	12
3 A PILOT STUDY: AN EXPERT SYSTEM TO ASSIST IN THE INTERPRETATION OF SONAR DATA	13
3.1 Background	13
3.2 Discussion of SAGE and CLASSIFY	14
CONCLUSIONS	19
REFERENCES	21
APPENDIX A — FRAME-BASED KNOWLEDGE REPRESENTATION	25
APPENDIX B — A PROPOSED ACTIVE-SONAR DISPLAY FORMAT FOR INTERFACING WITH AN EXPERT SYSTEM	29

List of Figures

1. Basic components of an Expert system.	3
2. Example of decision rule in "Classify".	16
3. Proposed block diagram for blackboard system.	18

ARTIFICIAL-INTELLIGENCE SYSTEMS IN ANTISUBMARINE WARFARE:
RESULTS OF A PILOT STUDY WITH EXPERT SYSTEMS

by

Ingemar J. Cox and Lewis J. Lloyd

ABSTRACT

Expert systems represent a programming methodology by which a computer can be instructed to perform tasks that have previously been considered to require the intelligence of a human expert. As such, it is anticipated that expert systems will have a major influence on future software design. The fundamental concepts of expert systems are explained and their current limitations and future potentials are described. Their application to ASW is examined and the military requirements for using such systems are discussed. In order to further explore the potential of these systems in ASW, and in particular in sonar signal processing, a pilot study has been run using the interpretation of active sonar data as an example. The main conclusion is that there is high potential for an expert system approach to the detection, tracking, and classification of active sonar data, and to other ASW tasks. Some aspects of the next phase of research are outlined.

INTRODUCTION

Research into artificial intelligence (AI) is concerned with the development of computers capable of performing tasks that at present require human intelligence. Since a precise or even generally acceptable definition of intelligence is difficult to arrive at, it is perhaps simplest to provide a list of the main areas of interest of AI researchers in order to clarify the goals and ambitions of artificial intelligence research.

Applied AI research is involved in:

- Speech understanding
- Perception or vision understanding
- Intelligent retrieval from databases
- Expert consultation systems
- Robotics
- Automatic programming
- Scheduling and combinatorial problems

This report is concerned with the application of expert consultation systems to ASW.

Historically, AI research began in the late 1950's with attempts to develop simple yet powerful general-purpose algorithms for problem solving. This power-based approach failed and has been superseded by a knowledge-based methodology, epitomised by "expert systems". Knowledge-based expert consultation systems are perhaps the most commercially successful development to originate from AI research and have provided a catalyst to the recent upsurge of interest in AI.

This three-part memorandum begins with a description of expert systems and their current limitations and future potential. Chapter 2 considers the possible applications of expert systems to ASW and provides a partial summary of previous naval research into AI. Chapter 3 summarizes the results of a pilot study on the application of an expert system to the interpretation of sonar data. The paper concludes with an outline of the recommended future research into AI within SACLANTCEN.

1 EXPERT SYSTEMS

1.1 Background

Tasks requiring intelligence can seldom if ever be described algorithmically. Instead, experts commonly describe their work as a collection of heuristics, i.e. informal judgemental rules or "rules of thumb". The modelling of such tasks using procedural languages such as FORTRAN or PASCAL is therefore very difficult. Moreover, small changes to the task domain can involve significant alterations to the program. Standard computer solutions to problems requiring intelligence have therefore proved elusive. However, this is now changing with the development of expert systems, which greatly simplify the construction of computer programs that are required to exhibit intelligence. Consequently, the area of expert systems is currently enjoying a large amount of interest.

Expert systems originated from research into artificial intelligence (AI); they may be defined as computer programs that exhibit similar performance to human experts in performing tasks — usually quite specialized tasks — that are normally considered to require intelligence. For example, expert systems have been developed for such diverse applications as mass spectroscopy analysis [1], medical diagnosis [2] — a program called MYCIN has been witnessed to outperform medical experts in the diagnosis and treatment of blood and meningitis infections — mineral exploration [3] — PROSPECTOR may have recently discovered mineral deposits worth \$100 000 000 — and speech understanding [4]. A reasonably complete list of expert system applications is provided in [5] and a more detailed discussion of those outlined above is in [6].

The successful demonstration of expert systems has stimulated commercial interest. The Digital Equipment Company (DEC), for example, now configures all its VAX computers using an expert system called R1 [7] and Schlumberger is involved in the development of expert systems to analyze oil-well dip meter and associated data [8]. More importantly, expert systems are expected to form a major part of the Japanese Fifth Generation Computer

Project. Consequently, expert systems methodologies are anticipated to exert a major influence on the development of future software. Moreover, this influence is expected to pervade all levels of computers, from the mainframe down to the personal microcomputer. Subsequent sections of this paper describe the fundamental concepts of expert systems and attempt to identify their current limitations and future capabilities.

1.2 Expert system frameworks

Expert systems consist of three distinct sections — a database, a knowledge source and an inference engine — as shown in Fig. 1. In fact, this structure is typical of AI programs in general.

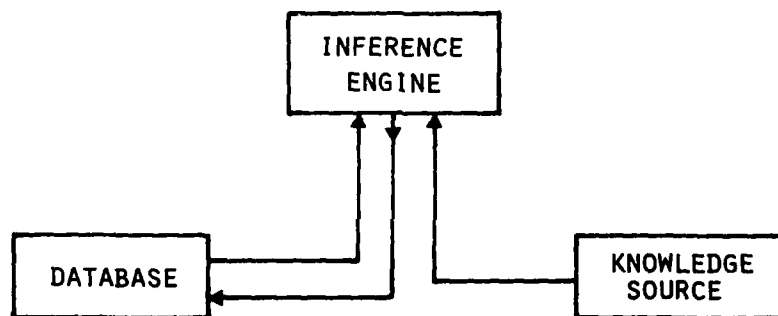


FIG. 1 BASIC COMPONENTS OF AN EXPERT SYSTEM

The database is nothing more than an area of memory in which all the program's variables are contained. To begin with, the database represents the initial data or facts from which the expert system is to infer some higher level information.

The key to this inference is the knowledge source that contains the necessary information to solve the problem. This information is obtained from (human) experts who, as stated earlier, describe their tasks not through algorithms but rather as a collection of heuristics represented in some manner within the knowledge source.

Because the expert's heuristics often resemble "rules of thumb", a common and popular method of encoding expertise is in the form of a collection of

IF <conditions> THEN <actions>

rules, otherwise termed production rules [9].

For example, in an expert system for computer-aided design [10] of electronic circuits, the knowledge that pin 20 of a 40-pin integrated circuit must always be connected to ground might be represented by

```
IF    <40 pin IC> AND
      <pin 20>
THEN  <connect to ground> .
```

It is important to realize that the framework described here is domain independent and only becomes domain dependent with the incorporation of the specific knowledge. A change in the knowledge is all that is needed to alter the problem domain.

Given an initial database and a collection of rules forming the knowledge source, the task of the inference engine is to select an applicable rule and apply it, subsequently modifying the database. The cycle repeats itself until a final assessment is reached.

Rule selection is often quite simple, the inference mechanism usually being data driven or demand (goal) driven. In the data-driven mode the condition part of each rule is checked against the database to establish its validity. The inference engine then selects and applies a rule from the set of rules whose conditions are satisfied. This selection may be performed on the basis of a rule's priority — provided by the expert — or, more usually, simply by the physical position of the rule within the set i.e. the first rule is applied. A data-driven procedure is then:

```
Database    initial data/facts
Do until databased satisfied goalstate
  Test the condition part of each rule against the
  database.
  Select a rule, say A, from the set of applicable
  rules.
  Apply rule A, modifying database.
End.
```

The demand-driven or goal-driven strategy is a top down approach in which rules are chained together such that the action parts of subsequent rules provide information concerning the validity of the condition part of the previous rule.

Both strategies have advantages. The choice of which control strategy to apply depends strongly on the nature of the knowledge source. In air-traffic control, for example, one might have a data-driven expert system for analysis of radar returns, and a goal- or expectation-driven expert system with knowledge of aircraft schedules, e.g., if flight 267 is expected then look to see if there is a corresponding radar contact.

Usually a combination of goal-driven and data-driven strategies, rather than one or the other, is to be preferred. Clearly, the control strategy of the inference engine is too simple to be responsible for the intelligent behaviour of an expert system. As Feigenbaum has stated [6], "The theme is that in the knowledge is the power. The interesting action

arises from the knowledge base, not the inference engine". In fact, expert systems are also referred to as knowledge-based systems.

Although an expert system need only possess the three characteristics of a database, knowledge source, and inference engine, the addition of an explanatory facility is usually requisite. This is because expert systems are frequently applied to areas in which computer assistance is uncommon and the very fact that they claim to be capable of performing tasks previously requiring the intelligence of a human experts creates both suspicion and resentment of such systems. Ultimately an expert system must be accepted by users if it is to be considered successful. Consequently, it is imperative that the user interface be as friendly as is (economically) possible. Questions should be presented in natural English and, where possible, replies should be accepted in "natural" language or via graphic and/or menu-driven input.

Most important of all, it is critical that the expert system be capable of explaining why a question is being asked and how it has arrived at its conclusion. Explanations can be provided by simply sequentially listing the set of rules that were applied or by producing a list of the current goals. More sophisticated explanatory facilities can even involve an additional expert system.

In fact, it is becoming increasingly common to develop multiple expert systems that allow a more modular and structured representation of diverse knowledge sources. Following [4], such systems are often termed blackboard systems, in which the individual expert systems communicated via a "blackboard".

1.3 Limitations of expert systems

Although the possible application domain of expert systems is very broad, there are several hurdles that must be overcome before their full potential is achieved. Perhaps the four most difficult problems relate to (1) knowledge engineering, i.e. the acquisition of the rules, (2) the modelling of uncertainty within an expert system, (3) the representation of knowledge and, in particular, the representation of common-sense knowledge, and (4) problems related to the control strategy within the inference engine. These limitations are described in more detail below, with comments on their possible future solution.

1.3.1 The knowledge engineering problem

The acquisition of an expert's knowledge, i.e. knowledge engineering, is a serious hurdle to the development and performance of expert systems.

An expert system's performance can be very high. For example, in certain test cases, MYCIN has been witnessed to outperform acknowledged medical experts [11]. This is not altogether surprising, since MYCIN's rule-base is based on the combined experience of many experts and might therefore be expected to be superior to any one expert. However, it is still a remarkable result that is both a credit to MYCIN's designers and a demonstration of the potential power of the expert-systems approach.

Of course, a model's performance is ultimately limited by the quality of the rules provided. Thus, in the case of DENDRAL, while its performance is generally at the level of a senior graduate student in analytic chemistry, it is said that in some cases "the program's behaviour is truly exceptional" [12].

This highlights an important implementation problem for expert systems, which is the acquisition of the heuristic rules from the expert. Many people who are considered experts in their field of work find it extremely difficult to explain in detail how they arrive at their assessment. Moreover, an expert may not even be explicitly aware of all the processes by which he performs his work. Rule acquisition is such a problem that Feigenbaum et al [12] reported that "knowledge acquisition is the pace-setting factor in DENDRAL's further development".

In these situations, the development of expert systems can often result in the formalization of a domain of knowledge that was previously vague, and can even provide an expert with additional insight into his subject. Of course these benefits assume that one can extract the relevant knowledge from the expert. Clearly there is an urgent need to automate this process. Two different solutions to this problem have been explored: interactive rule acquisition and automatic rule acquisition through "learning".

Interactive rule acquisition is typified by a program called TEIRESIAS [13]. Here an expert engages in a consultation with the expert system. If the expert should disagree with the system's final conclusion, TEIRESIAS explains to the expert how this conclusion was reached and requests from the expert a new or improved rule to upgrade the system's knowledge base.

Automatic rule acquisition, on the other hand, requires no expert, but only a large data set from which to induce the heuristic rules. Machine learning via induction has been successfully applied to mathematics [14] and chemical crystallography, where the Meta-DENDRAL program [1,15] successfully discovered new fragmentation rules for mono-, di- and trike-toandrostanes.

Although automatic rule acquisition is to be preferred, induction procedures are not always possible, since in many domains test data simply may not be available. In such circumstances interactive rule acquisition has an important part to play. At present, however, both techniques are relatively immature, although in the future they are expected to provide a significant aid to the development of expert systems.

1.3.2 Probability and possibility

In almost all expert systems there is the need to handle uncertainty. This may be a consequence of noisy data, but, most often, is simply a reflection of the fact that the rules are judgemental and are describing the likelihood of an event given incomplete evidence. Uncertainty can be incorporated into a rule by simply providing a numerical value for the degree of certainty. Thus a typical rule in an expert system for automated circuit repair might be

```

IF  <the databus is idle> AND
    <there is no interrupt state>
THEN <the clock oscillator is likely (0.7) to be faulty>.

```

The number (0.7) represents the degree of certainty of the hypothesis. Although this figure can be a probability value there is often no mathematical basis for the probability estimate, simply an intuitive guess. Under these conditions, the use of Bayesian probability theory to represent uncertainty has often been found unsatisfactory. In particular, classical probability theory has been criticized for:

- (a) Its single-value representation, which is insufficient to indicate the accuracy of the estimated probability. For example, the probability value 0.7 ± 0.1 can provide a completely different interpretation from the probability value 0.7 ± 0.3 .

and

- (b) A single probability value, even if accompanied by a measure of its accuracy, cannot discriminate between lack of evidence and conflicting evidence. Discrimination of this sort can be important. Yet whilst a probability value of 0.3 indicates that an hypothesis is unlikely, it is impossible to infer whether this is because of lack of evidence to support the hypothesis or because of strong but conflicting evidence.

Several possibility theories have been proposed to address these problems, most of which are well summarized by Quinlan [16]. Although many of these theories have been implemented, no single one appears to be significantly better than all others. In fact, it has been hypothesized [17] that, an "exact" theory of possibility may not exist.

The main problem with current possibility theories is not that they do not work — MYCIN satisfactorily handles uncertainty — but that they do not satisfactorily reflect human understanding of uncertainty. The problem is therefore as much psychological as it is mathematical, and although it may prove intractable it is not expected to be too serious a hindrance to the future development of expert systems.

1.3.3 Problems of control

The representation of uncertainty within the knowledge base introduces a problem for the control strategy of an expert system. This is because the conditional part or premise of a rule is usually no longer true or false but a certainty value itself. The applicability of the rule is now no longer obvious. In such cases, if the degree of certainty of the premise is above an (arbitrary) threshold then the rule is usually said to be applicable. Of course the degree of certainty associated with the rules conclusion must now be weighted — again in some arbitrary manner — to reflect the degree of certainty in the premise.

More fundamental is the problem of rule selection. Data-driven and goal-driven strategies apply very simple selection criteria, which often lead

14. LENAT, D.B. and HARRIS, G. Designing a rule system that searches for scientific discoveries. In: WATERMAN, D.A. and HAYES-ROTH, P., Pattern-Directed Inference Systems. eds. New York, NY, Academic Press, 1978: pp. 25-51. [ISBN 0-12-737550-3]
15. BUCHANAN, B.G., SMITH, D.H., WHITE, W.C. et al Applications of artificial intelligence for chemical inference, 22: Automatic rule formation in mass spectrometry by means of the META-DENDRAL program. Journal of the American Chemical Society, 98, 1976: 6168-6178.
16. QUINLAN, J.R. INFERNO: A cautious approach to uncertain inference. Computer Journal, 26, 1983: 255-269.
17. SHAPIRO, E.Y. Logic programs with uncertainties: A tool for implementing rule-based systems. In: BUNDY, A., ed. Proceedings of the Eighth International Joint Conference on Artificial Intelligence, 8-12 August, 1983, Karlsruhe, West Germany, volume 1. Los Angeles, CA, William Kaufmann Inc., 1983: pp. 529-532. [ISBN 0-86576-064-0]
18. MINSKY, M. A framework for representing knowledge. In: WINSTON, P.H., ed. The Psychology of Computer Vision. New York, NY, McGraw-Hill, 1975: pp. 211-280. [ISBN 07-071048-1]
19. NII, H.P. Signal-to-symbol transformation: A summary of HASP/SIAP case study (sonar data). In: INSTITUTE OF ELECTRICAL AND ELECTRONICS ENGINEERS. Intellectual Leverage for the Information Society. COMPCON 83, San Francisco, CA, 28 February-3 March 1983. Piscataway, NJ, IEEE, 1983: pp. 120-125.
20. CLARK, K.L. and TARNLUND, S.-A. Logic Programming. New York, NY, Academic Press, 1982. [ISBN 0-12-175520-7]
21. NILSSON, N. Principles of Artificial Intelligence. Berlin, Springer, 1982.
22. Computer, 16, (10), 1983. Special issue on knowledge representation.
23. CALLERO, M., GORLIN, D., HAYES-ROTH, F. and JAMISON, L. Toward an expert aid for tactical air targeting, N-1645-ARPA. Santa Monica, CA, Rand Corporation, 1981.
24. CALLERO, M., JAMISON, L. and WATERMAN, D.A. TATR: An expert aid for tactical air targeting, N-1796-ARPA. Santa Monica, CA, Rand Corporation, 1982. [AD A 113 583]
25. MASUI, S., McDERMOTT, J. and SOBEL, A. Decision making in time critical situations. In: BUNDY, A., ed. Proceedings of the Eighth International Joint Conference on Artificial Intelligence, 8-12 August, 1983, Karlsruhe, West Germany, volume 1. Los Angeles, CA, William Kaufmann Inc., 1983: pp. 233-235 [ISBN 0-86576-064-0]

REFERENCES

1. BUCHANAN, B. and FEIGENBAUM, E.A. DENDRAL and META-DENDRAL: their applications dimension. Artificial Intelligence, 11, 1978: 5-24.
2. SHORTLIFFE, E.H. Computer-based Medical Consultations: MYCIN. Amsterdam, Elsevier, 1976. [ISBN 0-444-00179-4]
3. DUDA, R., GASCHNIG, J. and HART, P. Model design in the PROSPECTOR consultant system for mineral exploration. In: MICHIE, D., ed. Expert Systems in the Micro-electronic Age. Edinburgh, Edinburgh University Press, 1979: pp. 153-167. [ISBN 085224 4932]
4. ERMAN, L., HAYES-ROTH, F., LESSER, V. and REDDY, D. The HEARSAY-II speech understanding system: Integrating knowledge to resolve uncertainty. Computer Surveys, 12, 1980: 213-253.
5. GEVARTER, W.B. Expert systems: powerful but limited. IEEE Spectrum, 20, (8), 1983: 39-45.
6. FEIGENBAUM, E.A. Themes and case studies of knowledge engineering. In: MICHIE, D., ed. Expert Systems in the Micro-electronic Age. Edinburgh, Edinburgh University Press, 1979: pp. 3-25. [ISBN 085224 4932]
7. McDERMOTT, J. R1: A rule-based configurer of computer systems. Artificial Intelligence, 19, 1982: 39-88.
8. SMITH, R.G. and BAKER, J.D. The DIPMETER ADVISOR system. A case study in commercial expert system development. In: BUNDY, A., ed. Proceedings of the Eighth International Joint Conference on Artificial Intelligence, 8-12 August, 1983, Karlsruhe, West Germany, volume 1. Los Angeles, CA, William Kaufmann Inc., 1983: pp. 122-129. [ISBN 0-86576-064-0]
9. DAVIS, R. and KING, J. An overview of production systems. Machine Intelligence, 8, 1976: 300-332.
10. STEFIK, M.J. and de KLEER, J. Prospects for expert systems in CAD. Computer Design, 22, (5), 1983: 65-76.
11. YU, V.L., FAGAN, L.M., WRAITH, S.M. et al. Computerized consultation in antimicrobial selection - a blinded evaluation by experts. Journal of the American Medical Association, 242, 1979: 1279-1282.
12. FEIGENBAUM, E.A. and ENGELMORE, R.S. A correlation between crystallographic computing and artificial intelligence research. Acta Crystallographica, A33, 1977: 13-18.
13. DAVIS, R. Interactive transfer of expertise: acquisition of new inference rules. Artificial Intelligence, 12, 1979: 121-157.

Naturally, emphasis will be placed on the interface with the active sonar, and tape-recordings will be used initially to develop the required data link and control. One aspect of considerable importance in this respect will be the format used for the active sonar display. Currently this is a B-scan format, on which one attempts to display five parameters: range, bearing, signal level, time, and doppler shift. The image produced is not a contiguous image in a conventional spatial form, and consequently little, if any digital image processing can be performed on this type of sonar display. Appendix B outlines a form of sonar display, referred to as C-scan, that is based on the PPI format. It is proposed that this be considered in the future research as a means of simplifying and enhancing the sonar interface.

CONCLUSIONS

The problems encountered in the design and development of CLASSIFY (Ch. 3) support many of the general conclusions discussed in Ch. 1. In particular, problems associated with:

- uncertainty
- control strategies
- knowledge acquisition

can become so serious as to hinder further development of an expert system.

However, although serious problems do exist, the general conclusion must be that the methodology of expert systems provides a simple yet powerful method for developing software for heuristic rather than algorithmic tasks. Since many naval and ASW tasks are described, at least in part, by "rules of thumb", expert systems are anticipated to become increasingly important as expert decision-support systems.

At SACLANTCEN the initial phase of continuing research into expert systems will consist of rewriting the SAGE version of CLASSIFY using the SPL MXA blackboard system software (Sect. 3.2.2). This will give the Centre a major step forward into the particular area of blackboard systems (just as SAGE has done for basic expert systems). It will allow us to assess and evaluate the pros and cons of the application of the blackboard structure in general to the task of interpreting active sonar data in the multi-sensor environment of a typical operational sonar. Guidelines for formulating a real-time system should also emerge.

It is concluded that the study of the interface with a typical operational sonar must await the evaluation of the blackboard system. In addition, a pre-requisite is a detailed study of the pre-processing of the data needed for processing by the expert system. In this respect App. B outlines an appropriate line of approach to allow the use of conventional digital image-processing techniques for simplifying the sonar interface.

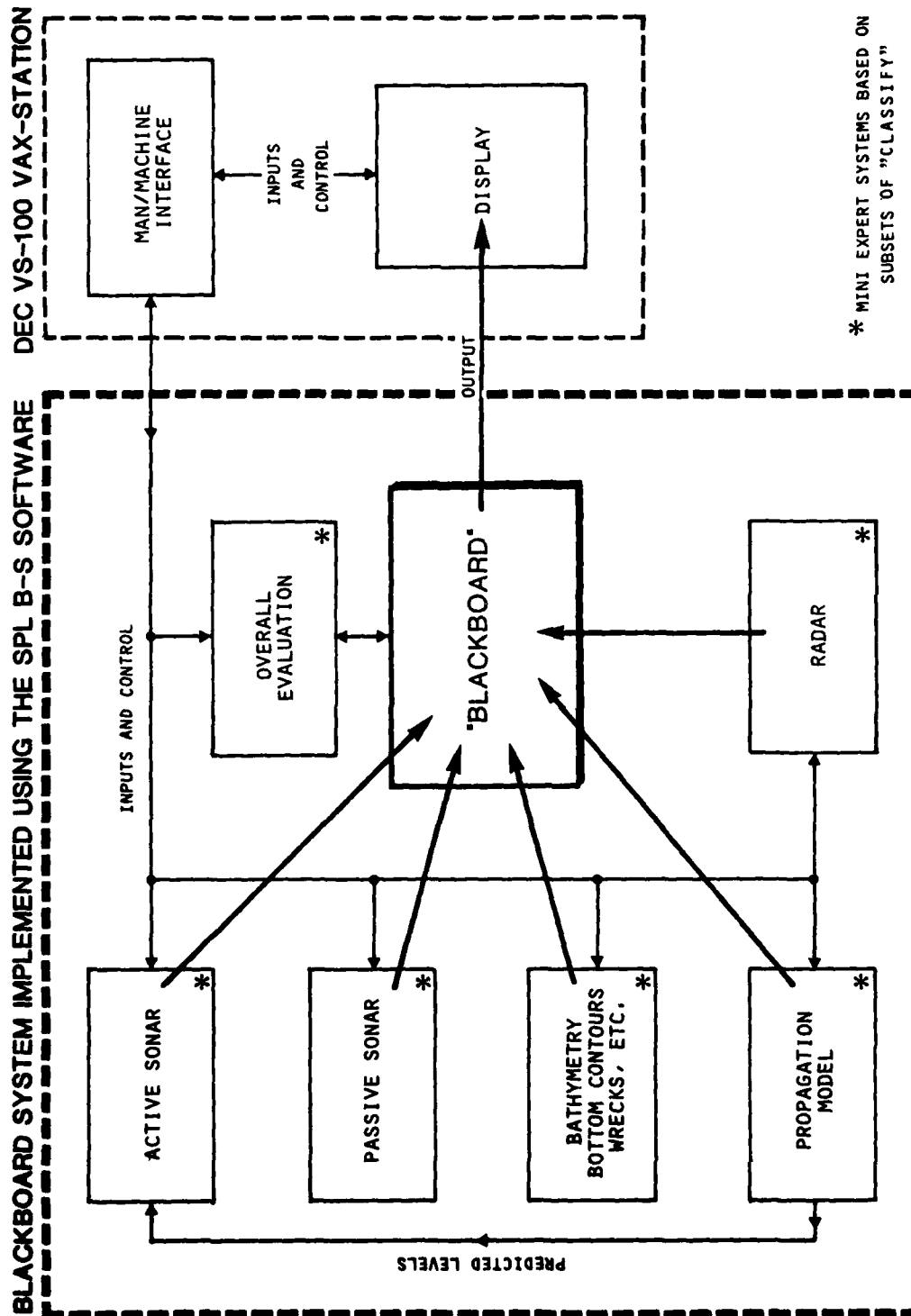


FIG. 3 PROPOSED BLOCK DIAGRAM FOR BLACKBOARD SYSTEM

task. This is particularly the case with CLASSIFY because SAGE does all its decision work in "degrees of belief" that are not linearly related to probability. Thus to tune and refine the weights in CLASSIFY a technique has been developed that is almost heuristic.

For example, we have argued that an echo cannot be fully classified on a single ping; consequently the sum of all the positive weights for any major goal must not give a high probability for a single ping. On the other hand, some of the weights can be quite large, because, for example, the occurrence of a passive contact relating to a snorkelling submarine must give strong support to the presence of a submarine. Similarly the lack of a radar echo must strongly deny the presence of a surface ship. Additionally, when an evidence factor is used in more than one major goal the weights must be adjusted according to the relative importance of the evidence in each goal.

There are two important aspects of using an expert system to assist a sonar operator that have not been considered in depth in the pilot study:

- a. The requirement for the expert system to run in real-time; that is, in the case of an active sonar, to complete its evaluation during the transmission interval.
- b. The interface of the expert system with an actual sonar system, including such ancillary equipments as radar, navigation system, etc.

Obviously these two topics will occupy some proportion of the effort in the future research. With regard to (a), CLASSIFY takes approximately 3 min on a VAX-750 to fully analyze one range and bearing cell. This is far from real-time. However, one major reason for this long period is the sequential nature of the operations of the SAGE software. CLASSIFY evaluates a number of "areas" of input information sequentially to obtain numerical values for the evidence factors. Then it assesses the possible presence of some 13 objects, again in a sequential manner.

The use of a blackboard structure of expert systems would allow these evaluations to be progressed in parallel, thus reducing the running time by a factor of at least ten for a SAGE-based blackboard system on the VAX-750. One would then need to decide how many range-and-bearing cells need to be evaluated in each transmission interval, since it would be possible to examine only those that are of high interest. It has been decided to use the SPL (MXA) blackboard system in the next phase of the research. This system was developed by SPL for the UK Admiralty Research Establishment, Portsmouth, in connection with their studies into expert systems to assist operators of radar tracking systems. This software framework will be installed in SACLANTCEN's VAX-750 and the first task of the next phase of research will be to rewrite CLASSIFY using the blackboard-system software along the lines indicated by the block diagram in Fig. 3.

In the case of (b) above it is considered that the in-depth study of the interface must await the evaluation of (a) and the gaining of experience with a blackboard system. This arises since the eventual requirement will be to interface a blackboard system with a typical on-board sonar/sensor system.

ASSERTION Prior-pinnacle:
 "Influence of findings for pinnacle from last run"
 ASKABLE

RULE Eval-prior-pinnacle:
 "Rule to determine prior influence for pinnacle"
 Prior-pinnacle IS (Fn-prior-pinnacle ())/2.0)

RULE Eval-1-pinnacle: "This rule looks to see if there is a"
 "charted pinnacle in the data base"
 Pinnacle IS True
 PROVIDED Known-pinnacle = True

RULE Eval-2-pinnacle: "This rule looks to see if it thinks"
 "that it is looking at a pinnacle"

Pinnacle	DEPENDS ON			
Submerged	AFFIRMS	8.0	DENIES	-10.0,
Passive-contact	AFFIRMS	-10.0	DENIES	5.0,
Known-pinnacle	AFFIRMS	15.0	DENIES	-10.0,
Echo-significant	AFFIRMS	- 2.0	DENIES	0.0,
Echo-strength	AFFIRMS	8.0	DENIES	0.0
PROVIDED (Speed < 2)	AND (NOT(Island))			

RULE Eval-3-pinnacle: "This rule says that it can't be a"
 "pinnacle"
 Pinnacle IS False

FIG. 2 EXAMPLE OF DECISION RULE IN "CLASSIFY"

Evidence-1 AFFIRMS W_{A1}	DENIES W_{D1}
:	:
:	:
Evidence-N AFFIRMS W_{AN}	DENIES W_{DN}

Here $I(X)$ is the starting value of probability for the rule. Thus if there is some prior knowledge of the presence of X this prior value can be inserted. Otherwise a default value, equivalent to saying that there is no prior knowledge, is automatically selected by SAGE. The W 's are weighting factors representing the degree of importance that an evidence factor has in affirming or denying the presence of X . These weights must be defined by the "expert". A typical rule from CLASSIFY is shown in Fig. 2.

This form of weighted-evidence technique is a common approach to the evaluation of a major goal and has a number of drawbacks, as described in Ch. 1. In fact it is in connection with this "rule" that the biggest difficulties have been encountered with CLASSIFY. Firstly, the "expert" formulating the model has to decide what "characteristics" relating to a submarine he wishes to use as evidence factors to describe the submarine. A very good one would obviously be "visual sighting", but in the situations we are considering the occurrence of such evidence will be very sparse. Since we are dealing with an active sonar let us list some of the "evidence" we may have that could directly characterize a submarine, for example:

- Echo excess
- Echo characteristics
- Doppler shift
- Bearing rate

and indirectly

- Radar echo not present
- Passive contact held
- No bottom feature in the range-and-bearing cell
- No wreck in the range-and-bearing cell.

Consequently, the expert could use the above evidence as it stands or could use combinations of evidence; for example, doppler-shift could be combined with bearing-rate to give "true speed".

It can be seen from the above that different experts could easily select different evidence factors to evaluate the same goal. In fact the evidence is being specified in a heuristic manner and probably one requires a large number of experts to arrive at a really satisfactory rule. This issue was side-stepped in the formulation of CLASSIFY, since only a single "expert" (one of the authors, LJI) produced the rules. The second problem associated with this decision rule relates to the selection of values for the "affirms" and "denies" weights, and this seems to be an even harder

3.2 Discussion of SAGE and CLASSIFY

3.2.1 SAGE Framework

SAGE is a software framework for building and running expert systems. To the user/programmer, SAGE appears to be simply a very high level programming language and, as such, is easy to use. SAGE uses a combination of Boolean logic, fuzzy logic, and Bayesian probability to provide the user with a confidence factor for each assessment. It is thus capable of dealing with noisy data and uncertainty and, at the limit, can assume default values for parameters and continue with an assessment. A very valuable facility of SAGE is its ability to interface to FORTRAN or PASCAL subroutines. Mathematical algorithms and databases can therefore be dealt with conventionally, with SAGE being used only for the heuristic analysis.

SAGE provides a simple expert system framework. As such, it has no facilities for local or global variables, and no directly accessible 'free' memory — any 'storage' of data must be done by FORTRAN. We have found compiling the knowledge base to be slow and the error indications to be particularly weak. However, in use, SAGE has proved to be robust when mishandled and has a number of useful built-in test facilities. For example, it can provide a graphical description of the variation of a Bayesian decision rule (see below) as a function of one of the evidence factors. Another useful facility is the WHY command, which causes the system to explain why it requires an answer to the question.

Although SAGE was found to be a user-friendly development system and easy to program, there are several deficiencies with the current framework. These include:

- An inflexible goal-directed control strategy
- A lack of modularity.

Neither of these problems is particularly difficult if only small expert systems, i.e. less than 100 rules, are to be developed. However, the lack of modularity is a particular hindrance to the development of large systems. Moreover, as discussed in Ch. 1, there is a need for expert systems to provide for both demand-driven and data-driven control. Consequently, it is unlikely that SAGE will be used to develop any large expert system.

3.2.2 CLASSIFY System

CLASSIFY is the expert system structured on the SAGE framework for the interpretation and classification of simulated active-sonar data.

Within CLASSIFY, or any SAGE model for that matter, the evaluation of a major goal is performed using a Bayesian probability rule of the form:

X DEPENDS ON

PRIOR (DEFAULT) VALUE IS I(X)

3 A PILOT STUDY: AN EXPERT SYSTEM TO ASSIST IN THE INTERPRETATION OF SONAR DATA

3.1 Background

In order to explore the potential of expert systems in ASW, and in particular, in sonar signal processing, a pilot study has been run using the interpretation of active sonar data as its task.

Commencing research into the application of expert systems is awkward and somewhat risky at present, since it is a very new discipline that, as yet, has no established standards. Because SACLANTCEN is concerned with the application of AI methodologies, it was decided to commence research using a commercially available expert-system software framework. A system available from SPL Abingdon, UK, (called SAGE) was chosen; this is written in PASCAL and runs on the Centre's VAX computers.

A pilot study using SAGE has been carried out to provide an understanding of the problems of developing and interfacing an expert system. The result of this study is an expert system (called CLASSIFY) for the interpretation and classification of active-sonar data assuming a typical onboard environment with information also being available from passive sonar, radar, etc. As such, the system may be regarded as an expert decision-support system. At this stage no attempt has been made to interface CLASSIFY with an actual sonar system; consequently all the inputs are simulated.

Interpretation of sonar data is becoming increasingly difficult as modern sonars continue to present increasing amounts of target-like data and as discrimination of target signals becomes more difficult. Attempts to provide computer assistance to the sonar operator have been hindered by an inability to describe the interpretation process mathematically. In fact, sonar interpretation is commonly acknowledged to be more of a black art than a science. Recognition of this has led to interest in expert systems in order to model the sonar operator's "rules of thumb".

The heuristic rules are a combination of the sonar operator's specific experience in the use of a particular sonar and of prior knowledge, for example the expected size of an echo relative to a range and bearing cell. In addition, data available from other sensors and from navigational chart can be invaluable. For example, the presence of a radar echo from the same range and bearing cell as a possible echo must reinforce the hypothesis that a target is present.

During the pilot study, two expert systems were formulated and implemented for the above task based on the use of simulated inputs. The second of these systems, CLASSIFY, is a more structured expert system currently in use at the Centre. It can be operated in an interrogative mode or by an input file; it is comprehensively self-documented and is available for any VAX user.

The subsequent sections outline our experiences in using CLASSIFY, detailing some of the problems encountered. Finally, the conclusions of the pilot study and a detailed proposal for future research at SACLANTCEN are presented.

because the representation of uncertainty within expert systems, whilst essential and fundamental to their operation, greatly increases the difficulty of such tests. Moreover, the development of a general-purpose testing procedure is hindered by the lack of a single accepted possibility/probability/uncertainty scheme. Unless a proof of correctness can be given it is unlikely, indeed unwise, for expert systems to replace military specialists, although their decision support role will still be very valuable.

The simple operation of current control strategies will require improvement if expert systems are to perform adequately in a military environment. In particular, the assignment of a cost function to each rule may be necessary. For example, before requesting data to be obtained from a reconnaissance flight, an expert system ought to consider the cost of obtaining these data in comparison with the cost of an alternative solution, say radar. Even more important, meta-knowledge will be required to choose the most important objective for immediate analysis, given a current set of conditions - it is obviously more important to complete the assessment of a submarine at 10 km than that of a ship at 100 km.

2.4 Near-future military applications

Whilst work on future expert systems with real-time performance and sophisticated control strategies is encouraging [32], there has been less success at completeness, consistency, and correctness tests. However, the overall conclusion to be drawn from current research and development in expert systems is that such systems can be expected to become increasingly important military applications.

Specific AS applications are considered to be in:

- a. Command and control, e.g. tactical assistance for search and evasion plans, and for weapons and countermeasures control
- b. Intelligence, e.g. data management of reconnaissance information
- c. Signal interpretation, e.g. assistance in passive and active sonar data analysis (see Ch. 3)

and, somewhat more general,

- d. Expert systems might provide useful decision support systems for supply and maintenance of naval vessels.

Summarizing, expert systems in the form of decision-support systems are anticipated to proliferate throughout all three forces of the military. Although such systems may not replace military specialists, expert decision-support systems will provide much needed assistance in the interpretation of ever-increasing quantities of information. Moreover, these systems ought to provide for a more consistent operation, being most useful when specialist operators are suffering from tiredness and fatigue or simply from information overload.

"In signal-processing applications, involving large amounts of data with poor signal-to-noise ratio, it is possible to reduce computational costs by several orders-of-magnitude by the use of knowledge-based reasoning rather than brute-force statistical methods. We estimate that HASP/SIAP can reduce computation costs by two to three orders-of-magnitude over conventional methods. It makes little sense to use enormous amounts of expensive computation to tease a little signal out of much noise, when most of the understanding can be readily inferred from the symbolic knowledge surrounding the situation..... The intelligent combination of AI and signal processing views the signal processing component as another knowledge source, with rules on how best to employ algorithms and how to interpret their output".

Finally, expert systems may also be used in a teaching role to assist in the training of military personnel. In this regard, the work by Chatfield and Klein on the role of AI in voice-based training systems [30] is of interest.

This partial literature survey clearly shows that expert systems have an important role to play in the development of advanced military software. Already, several systems have been developed and tested, to the extent that at least one is now undergoing field trials. However, military applications can place additional demands that complicate the design and development of expert systems.

2.3 Requirements for military expert systems

The additional demands placed on military expert systems are well discussed in [31]. Primarily, they are:

- a) A real-time requirement.
- b) A need to develop completeness, consistency, and correctness tests.
- c) More sophisticated control strategies, including:
 - (1) assignment of a cost function to the evaluation of a rule,
 - (2) incorporation of meta-knowledge to select most important current goal.

Real-time operation of expert systems is expected to be the least difficult of the requirements listed above. Past research has shown that expert system methodologies [25] can often be quicker than traditional procedural approaches, and, in fact, AIRPLAN is a real-time expert system already undergoing field trials. The size of expert systems will of course increase significantly in the near future and real-time operation may become more difficult. However, it is anticipated that within the next five years computer hardware in the form of LISP, or perhaps PROLOG, machines will offer order-of-magnitude improvements in processing speed.

At the other extreme, completeness, consistency and correctness tests for expert systems are expected to be very difficult to develop. This is

academic curiosity but provides a major set of software techniques that are particularly appropriate to common naval problems, including ASW.

The most common military application of AI has been to problems associated with command, control and intelligence, C²I. There appears to be no fundamental technical reason for this, rather, simply that C²I applications are intuitively obvious. Interesting research in this area includes:

- a) An expert system for tactical air targeting [23,24]. "Under interactive user direction, TATR preferentially orders enemy airfields, determines targets on those airfields to attack, and identifies the most effective weapon systems against those targets" [24].
- b) An expert system for the launch and recovery of aircraft from an aircraft carrier. AIRPLAN's "role is to accept raw data about the current situation (e.g., the fuel state of an airplane, the weather conditions at a possible divert site), propagate the implications of that data, alert the air-operations officer of possible impending problems, and make recommendations for how to resolve those problems" [25]. AIRPLAN is now in experimental use on the USS Carl Vinson.
- c) An expert system in the military intelligence area for "performing the indications and Warning Task: assimilating hundreds of incoming reports, and predicting where and when an armed conflict might erupt next" [26].

Signal processing, perhaps because of its traditional algorithmic approach, has taken longer to accept and incorporate knowledge-based methodologies. However, this is changing with the recognition that knowledge-based systems provide an excellent tool for integrating data from many diverse sources, i.e. for data fusion. Reducing the quantity of data presented by a signal/information processing system is becoming increasingly important since, all too often, the systems performance is degraded because the operator suffers from an information overload.

Several knowledge-based signal-processing systems have been developed, including:

- a) Two blackboard systems for the interpretation of passive sonar data, i.e., sonargrams [19,27,28].

and, at a somewhat higher level,

- b) An expert system, called STAMMER2, that "collects information by receiving messages and sensor reports (radar, electronic support measures, and sonar), and organizes these raw data into graphical displays and textual commentary to aid in tactical situation assessment" [29].

The advantages of a knowledge-based approach to signal processing are well summarized by M11 [19]:

slow. However, personal LISP machines are now entering the market and, although at present expensive, much research is being directed towards very cheap computers for efficient execution of expert-system software. Of course, this is one of the aims of the Japanese Fifth-Generation Computer Project.

It is anticipated that the near future will see the commercial application of expert systems not only as expert consultants but also in such technical areas as digital image processing and vision understanding, signal processing and speech understanding, and computer-aided design, including VLSI (very large integration) design.

The term "expert systems" may go as quickly as it came, but the software methodology, which is very similar to the declarative style of logic programming [20] typified by PROLOG, will certainly remain. Expert systems will have a significant impact not just within electronics and computer science but throughout society [21, 22]. Easy and inexpensive access to expert advice and knowledge from all areas of the arts and sciences can have little less than a revolutionary impact on society. Speculation as to the consequences of such a revolution must however, be postponed to a future paper.

2 APPLICATIONS IN ASW

2.1 Background

The ability of expert systems to solve problems whose solutions are not algorithmic or mathematical but predominantly a collection of heuristic rules, vastly increases the application domain for computers. Many naval and, more specifically, ASW problems fall into this heuristic category. As such, the potential application of knowledge-based expert systems to ASW is large. However, military applications can place significant additional requirements on the design of expert systems.

Section 2.2 provides a partial review of recent research and applications of AI to military use, of which a considerable amount has been sponsored by the US Navy. The additional military requirements that may be needed for some expert-systems applications are discussed in Sect. 2.3. Near-future, i.e. for immediate research and development, applications of expert systems to ASW are summarized in Sect. 2.4.

2.2 Previous Military-sponsored Research into Artificial Intelligence

The brief resume that follows is primarily based on an extensive on-line search of the open literature conducted from SACLANTCEN in the Lockheed DIALOG information-retrieval data base. More recent, current, and topical research may have been security-classified by individual NATO member countries and therefore not be available on the files searched. However, the principal reason for this summary is not to provide a complete historical perspective of the relationship between AI research and the navies but, more importantly, to demonstrate that AI is no longer an

to the application of inferior rules, inferior in the sense that there exists a more relevant applicable rule. This has lead to the introduction of what is termed meta-knowledge i.e. knowledge about knowledge. Meta-knowledge in the form of rules, such as:

```
IF      <A is known> AND
        <B is required>
THEN    <apply rule (6) first>
```

can be incorporated within the inference engine, which now begins to resemble a small expert system in itself.

1.3.4 Knowledge representation

The previous examples have represented an expert's knowledge as a collection of IF-THEN rules. Although this is adequate for expert systems that are applied to highly specific and narrow problem domains, when the problem becomes broader this rule-based representation becomes unsatisfactory. In particular, such systems begin to display a lack of "common sense". It is impractical to provide this "common sense" by the addition of further rules. Attempts to solve this problem have emphasized the need to structure data so that simple inferences are implicit within the representation (see App. A). Frame-based [18] structures have had success in achieving this goal and it is expected that frame-based knowledge representation languages will become common, particularly in large and sophisticated expert systems.

1.4 Future developments

Present applications of expert systems are within very narrow and highly specific problem areas. This is a consequence of the difficulty in representing knowledge and, in particular, common-sense knowledge. This is expected to change gradually, so that expert systems will possess increasingly broader knowledge of their problem domain.

Although rule acquisition is currently the major obstacle to the rapid development of expert systems, the successful development of automatic and interactive rule acquisition tools is expected to reduce the problem of knowledge engineering significantly.

Many current expert systems represent a very large software development and typically require a mainframe computer on which to run. However, commercial expert-system frameworks (such as the SAGE system marketed by SPL, Abingdon, uk) are already available that are capable of running on an Apple II microcomputer and the use of expert systems is anticipated to pervade all levels of computer hardware, from the mainframe down to the micro.

It is commonly thought that expert systems are inordinately slow. In fact this is a fallacy, and in some cases the use of an expert system rather than a traditional algorithmic approach has been demonstrated to be both cheaper and faster [19]. This is not to deny that some expert systems are

26. LENAT, D.B., CLARKSON, A. and KIREMIDJIAN, G. An expert system for indications and warning analysis. In: BUNDY, A., ed. Proceedings of the Eighth International Joint Conference on Artificial Intelligence, 8-12 August, 1983, Karlsruhe, West Germany, volume 1. Los Angeles, CA, William Kaufmann Inc., 1983: pp. 259-262. [ISBN 0-86576-064-0]
27. MAKSYM, J.N., BONNER, A.J., DENT, C.A. and HEMPHILL, G.L. Machine analysis of acoustic signals. In: CHEN, C.H., ed. Issues in Acoustic Signal-Image Processing and Recognition. Berlin, Springer, 1983: pp. 95-112.
28. NII, H.P., FEIGENBAUM, E.A. Rule-based understanding of signals. In: WATERMAN, D.A. and HAYES-ROTH, F., eds. Pattern-Directed Inference Systems. New York, NY, Academic Press, 1978: pp. 483-501. [ISBN 0-12-737550-3]
29. FERRANTI, J.P., Jr. Evaluation of the artificial intelligence program STAMMER 2 in the tactical situation assessment problem. Monterey, CA, Naval Postgraduate School, 1981. (thesis). [AD A 101 101]
30. CHATFIELD, D.C., KLEIN, G.L. and COONS, D. INSTRUCT: An example of the role of artificial intelligence in voice-based training systems, NAVTRAEQUIPC-80-C-0061. Lubbock, TX, Behavioral Evaluation and Training Systems. [AD A 124 126]
31. BEN-BASSAT, M. and FREEDY, A. Knowledge requirements and management in expert decision support systems for (military) situation assessment. IEEE Transactions on Systems, Man and Cybernetics, 12, 1982: 479-490.
32. SAUERS, R. and WALSH, R. On the requirements of future expert systems. In: BUNDY, A., ed. Proceedings of the Eighth International Joint Conference on Artificial Intelligence, 8-12 August, 1983, Karlsruhe, West Germany, Vol. 1. Los Angeles, CA, William Kaufmann Inc., 1983: pp. 110-115. [ISBN 0-86576-064-0]

APPENDICES

APPENDIX AFRAME-BASED KNOWLEDGE REPRESENTATION

In a frame-based knowledge representation, a class of objects/events/scenes is initially described by a prototype. This prototype is a stereotypical description of the class. For example, a prototype description of a gorilla might be

PROTOTYPE: Gorilla
 COLOUR: Brown
 SIZE: Large
 TEXTURE: Hairy

Each prototype has slots, e.g., COLOUR, SIZE, TEXTURE, which are typical characteristics of the class of objects. Slots may also have values that act as default values.

A particular example of a class is referred to as an instance of the class or an instantiation. The information that "King Kong is a gorilla" would then be represented as

KING KONG
 INSTANCE OF: Gorilla

Asked what colour King Kong is, the system would reply with brown, which is the default value provided by the prototype, even though no explicit information regarding the colour of King Kong was provided.

Property inheritance is also easily represented. For example, the fact that gorillas are mammals can be represented by altering the prototype:

PROTOTYPE: Gorilla
 INSTANCE OF: Mammal
 COLOUR: Brown
 SIZE: Large
 TEXTURE: Hairy

All the characteristics of mammals are now inherited by gorillas.

Simple deductive operations can also be performed using frame-based representations. Consider the information:

"Jane ate a peanut"
 and "King Kong ate whoever ate the peanut"

The information could be represented by a prototype

```

PROTOTYPE:   Eating events
EATER:
OBJECT:

```

and two instances

```

E1
INSTANCE_OF: Eating events
EATER:      Jane
OBJECT:      Peanut

```

and

```

E2
INSTANCE_OF: Eating events
EATER:      KING KONG
OBJECT:      EATER (E1)

```

Clearly, with such a representation, the answer to the question "Who did King Kong eat?" is easily deduced.

Obviously, it is not always possible to structure knowledge so usefully. However, rules may also be incorporated into a frame-based system. The prototype for a rule might be:

```

PROTOTYPE:   Rule
IF:
THEN:

```

A rule such as "if x works in department y and z is the manager of y, then z is the boss of x" might be represented as

```

R1
INSTANCE OF: Rule
IF:          (x works_in y)
AND:         (z Manager y)
THEN:        z boss_of x

```

Incorporating rules into the frame-based representation has the advantage that should a slot value within an instance be unknown, the default value in the prototype can actually be a call to a rule to infer the value. An illustration will help clarify this. Consider the prototypes:

```

PROTOTYPE:   Employee
NAME:
WORKS IN:
BOSS: R1

```

and PROTOTYPE: Manager
 NAME:
 DEPARTMENT:

and an instance of each such as:

E1
 INSTANCE_OF: Employee
 NAME: John
 WORKS_IN: Production
 BOSS:

and M1
 INSTANCE_OF: Manager
 NAME: Bob
 DEPARTMENT: Production

An attempt to answer "Who is John's boss?" finds the boss slot unknown and therefore attempts to use the default value provided by the prototype. Now, however, the prototype initiates the application of rule 1 above, which infers the correct value.

It is hoped that this superficial discussion has provided a flavour for the ideas and advantages of frame-based knowledge representations. The interested reader is directed to chapter 9 of [A.1] and to [A.2] for more detailed introductions to frame-based systems. A description of present state-of-the-art research in knowledge representation is in [A.3].

REFERENCES

- A.1 NILSSON, N. Principles of Artificial Intelligence. Berlin, Springer, 1982.
- A.2 MINSKY, M. A framework for representing knowledge. In: WINSTON, P.H., ed. The Psychology of Computer Vision. New York, NY, McGraw-Hill, 1975: pp. 211-280. [ISBN 07-071048-1]
- A.3 Computer, 16, (10), 1983. Special issue on knowledge representation.

APPENDIX BA PROPOSED ACTIVE-SONAR DISPLAY FORMAT FOR INTERFACING
WITH AN EXPERT SYSTEMINTRODUCTION

Data from active sonars comprise a large number of parameters — range, bearing, signal intensity, doppler shift, and time — that one would like to display simultaneously. At present, this is done using a B-scan format to produce a form of sonar image.

In the use of expert systems for the interpretation of sonar data, digital image processing could provide useful inputs. However, a B-scan "image" is not a contiguous image in a conventional spatial form, and consequently little, if any, digital image processing can be performed on it. Thus the B-scan format is not an optimum basis for interfacing a sonar to an expert system. The proposal made here is aimed at providing an active sonar format that:

- Displays all sonar parameters simultaneously,

and, more important,

- Uses a format that is very amenable to conventional digital image processing and thus can form a suitable basis for interfacing to an expert system.

Many, if not all, of the points detailed in this proposal have been implemented previously, although not necessarily combined into a single system. Consequently, much of this proposal is not original. However, it is felt that this C-scan format, as it is termed, would have many advantages.

The B-scan and PPI display formats are briefly described in Sects. B1 and B2. The proposed C-scan format is described in detail in Sect. B3. A brief reference to previous work is included with the conclusion.

B.1 B-Scan Display

Current active sonar displays use a B-scan format in which range is represented along the vertical axis and bearing-cell numbers are represented along the horizontal axis. Bearing cells do not vary continuously but are discrete, covering an arc generally equivalent to their 3 dB beamwidth. The width of each bearing cell does not correspond to a fine-bearing indication but is used to provide additional information. For example, the relative position of the displayed signal within the bearing cell can indicate the amount of doppler shift that is associated

with the signal. Alternatively, several ping histories can be displayed simultaneously, the most recent ping being represented by the rightmost signal within a bearing cell. In the latter case, the length of the recorded ping histories is limited by the finite width of the bearing-cell display.

There are several problems associated with the B-scan format. The most fundamental of these is the desire to simultaneously display five parameters: range, bearing, signal strength, time, and doppler shift. At present, a maximum of four of the five dimensions of the image are displayed using B-scan. The term "image" is used loosely here, since the B-scan format does not provide a contiguous image in a conventional (cartesian or polar) spatial format. Consequently, little, if any, digital image processing is, or can be, performed on B-scan sonar imagery.

B.2 Plan position indicators

Previous sonar displays have used a plan position indicator (PPI) format, now commonly used in radar displays, in which the target's position is displayed relative to one's own position. Traditionally, PPI target information was displayed within a polar co-ordinate framework, in which the origin represented one's own position. However, polar co-ordinates are not fundamental to the PPI format — a cartesian co-ordinate grid with one's own position at the centre of the grid would still represent a PPI format.

The immediate advantage of the PPI format is that it preserves the relative physical positions of the displayed target information. It is therefore more understandable and the fact that it is now a true image means that it is more amenable to digital image-processing techniques for enhancement and analysis purposes.

An alternative scan format, C-scan, is proposed, which has similarities with older PPI formats and uses colour and graphical and textual information to simultaneously display all five dimensions of an active sonar display.

B.3 C-Scan

The C-scan format is similar to the older PPI format in as much that it is proposed to display target information relative to the ship's or receiver's position. The receiver's position is, once again, represented at the centre of the display. The C-scan display therefore preserves the relative physical position of the acoustic information.

After beamforming, the detected acoustic signals are initially displayed in the PPI format. However, C-scan now requires the application of signal and/or digital image-processing algorithms in order to extract the most likely target signals. The phrase 'most likely' will not be qualified any further as it is expected that different sonar systems will search for possibly quite different targets with correspondingly different sonar characteristics. Typically, target signals might be selected by simple thresholding techniques or possibly by two-dimensional edge detection —

this emphasises relative changes in signal intensity — followed by thresholding. The number of target signals will not be qualified either. Once again, this is expected to depend on the particular sonar system, although a typical figure might be twenty.

After this processing is complete, the C-scan format displays only those selected target signals. Thus, after a single ping, the C-scan display might show twenty possible targets in their corresponding range/bearing cells. The intensity of each target point being proportional to the strength of the received acoustic signal.

It is now necessary to display the doppler shift associated with each of these targets. One proposed scheme is to associate discrete colours with discrete doppler shifts, the intensity of each individual colour being proportional to the signal's intensity. Unfortunately, the eye exhibits a nonlinear and highly complex response to colour/intensity variations, which is likely to cause some problems with this approach.

An alternative scheme is to associate a continuous colour mapping with the doppler frequency shift but not to display the signal intensity direct. This is assumed acceptable, since the signal amplitude will be much less important in a C-scan display, the information from this parameter being extracted by way of digital image processing.

Of course, there will be circumstances where knowledge of the signal intensity is necessary. On these occasions it is envisaged to allow the display to be interrogated — using a light pen or tracker ball, say — and for the requested information to be displayed in a textual format. Should this prove unsatisfactory, an alternative solution is to momentarily provide a raw PPI display illustrating the relative signal intensities.

To quickly digress, it is clear that C-scan will be much more sophisticated than traditional sonar displays. However, over the last ten years, display technology has progressed so rapidly that none of the current proposal will require any additional technological developments — all the necessary display hardware is commercially available.

The display of subsequent ping histories is relatively straightforward and is similar to that employed in radar: each ping is first processed as described previously, before being simply added or superimposed onto the display. The result is that moving targets "draw" lines on the display to represent their tracks. Stationary targets remain as points on the display, provided that one's own ship is stationary. Own-ship motion is dealt with later.

C-scan therefore has no fundamental limit to the duration of the ping history that can be displayed. In practice, the display is likely to become cluttered due to the accumulation of spurious "targets" and obsolete tracks. Periodic "garbage collection" is therefore necessary. This could be performed automatically using higher level image processing or it might be interactive with the user.

It has so far been assumed that one's own ship is stationary, although this would seldom be the case in practice. Own-ship motion can have a serious

effect on the C-scan display. Specifically, stationary targets exhibit tracks and real tracks are distorted because the origin, i.e., the own-ship's position within the C-scan display, is no longer fixed in real space. This effect occurs in B-scan displays and has not been found unacceptable. However, it is not felt necessary to preserve these distortions. In particular, "tracks" of stationary targets could be eliminated — again by higher level image processing — using the knowledge that such tracks do not possess any doppler shift. This would be a fairly simple procedure although it would be unable to deal with the distorted tracks of mobile vessels. A proposed solution is to use the American Global Position System, or Navstar, which allows a ship's position to be determined to ± 10 m and, more importantly, its speed to ± 0.1 ms. Such an accurate estimate of position and speed would allow complete nullification of ship motion for C-scan displays.

The nullification procedure is expected to shift all prior-recorded ping histories to new positions in the C-scan display to compensate for the displaced origin, before superimposing the current ping history. Thus, stationary targets remain as point targets and move across the display as one's own ship moves past them, whilst real tracks remain undistorted. With such a system it is then simple to provide latitude and longitude information around the display perimeter, which is periodically, say after every ping, updated.

SUMMARY AND CONCLUSION

The C-scan proposal outlined above is certainly too sophisticated (impractical?) to be completely implemented immediately. However, the potential of C-scan appears to be high. Most likely, C-scan implementation would start by:

- Displaying a single ping history in the PPI format.

If this is effective, it would progress to:

- Displaying ping histories in a C-scan format and attempting digital image processing for target and track detection.

Finally, when feasible, it would:

- Implement ship motion nullification.

Much work on displays has, of course, been performed. Discussions on the use of colour can be found in [B.1, B.2, B.3]. Other psychological characteristics related to displays — including the fact that an observer will always spend more time analyzing data at the centre of the display than data at the perimeter — are given in [B2]. The C-scan format is preferable to B-scan in this regard, since objects/targets close to one's own ship, i.e., those with the highest potential threat, are displayed nearest the centre of the screen.

Digital image processing of acoustic images is discussed in [B.4]; interestingly, the data are displayed in an x-y format. C-scan has a very similar format to that used in [B.5] for displaying data obtained from a low-frequency active towed array.

REFERENCES

- B.1 PRATT, W.K., Digital Image Processing. New York, N.Y., Wiley, 1978. [ISBN 0-471-01888-0]
- B.2 WALTERS, L.C., Notes on conclusions from work on displays, Report no. 72/79/41. Templecombe, UK, Plessey, Marine Research Unit, 1979.
- B.3 FRENCH, R.S., Grey-scale versus color coding of acoustic data images, NOSC TR 207. San Diego, CA, Naval Ocean Systems Center, 1978. [AD A 061 646]
- B.4 ROESE, J.A., Two-dimensional processing for acoustic signal space imagery, NOSC TR 337. San Diego, CA, Naval Ocean Systems Center, 1978. [AD A 066 041]
- B.5 ERSKINE, F.T., BERNSTEIN, E.R. FRANCHI, Imaging techniques for analysis of long range acoustic backscatter data from ocean basin regions. In: TOLLIOS, C.D., McELROY, M.K. and SYCK, J., eds. Proceedings, third working symposium on oceanographic data systems, Woods Hole Oceanographic Institution, October 4-6, 1983. Sponsored by IEEE Computer Society and Woods Hole Oceanographic Institution. Piscataway, NJ, IEEE, 1983: pp. 160-164.

KEYWORDS

ACTIVE SONAR
ARTIFICIAL INTELLIGENCE
CLASSIFICATION
CLASSIFY
DETECTION
EXPERT SYSTEMS
HEURISTIC RULES
KNOWLEDGE BASED SYSTEM
SAGE
SONAR SIGNAL PROCESSING
TRACKING

SACLANTCEN SN-176

INITIAL DISTRIBUTION

	Copies		Copies
<u>MINISTRIES OF DEFENSE</u>		<u>SCN FOR SACLANCEN</u>	
JSPHQ Belgium	2	SCN Belgium	1
DMV Canada	10	SCN Canada	1
CMO Denmark	8	SCN Denmark	1
MOB France	8	SCN Germany	1
MOB Germany	15	SCN Greece	1
MOB Greece	11	SCN Italy	1
MOB Italy	10	SCN Netherlands	1
MOB Netherlands	12	SCN Norway	1
CMO Norway	10	SCN Portugal	1
MOB Portugal	2	SCN Spain	1
MOB Spain	1	SCN Turkey	1
MOB Turkey	1	SCN U.S.	20
MOB U.S.	20	SCN USSR	1
MOB USSR	1		

NAVY DEPARTMENT

Naval Planning Committee

SECDEF

SECNAV

SECSTATE

SECDEF/SECNAV

SECDEF/SECNAV

SECDEF/SECNAV

SECDEF/SECNAV

SECDEF/SECNAV

SECDEF/SECNAV

SECDEF/SECNAV

SECDEF/SECNAV

SECDEF/SECNAV

SECDEF/SECNAV

SECDEF/SECNAV

SECDEF/SECNAV

SECDEF/SECNAV

SECDEF/SECNAV

SECDEF/SECNAV

SECDEF/SECNAV

SECDEF/SECNAV

SECDEF/SECNAV

SECDEF/SECNAV

SECDEF/SECNAV

SECDEF/SECNAV

SECDEF/SECNAV

SECDEF/SECNAV

SECDEF/SECNAV

SECDEF/SECNAV

SECDEF/SECNAV

SECDEF/SECNAV

SECDEF/SECNAV

SECDEF/SECNAV

SECDEF/SECNAV

SECDEF/SECNAV

ATE
LMED
-8