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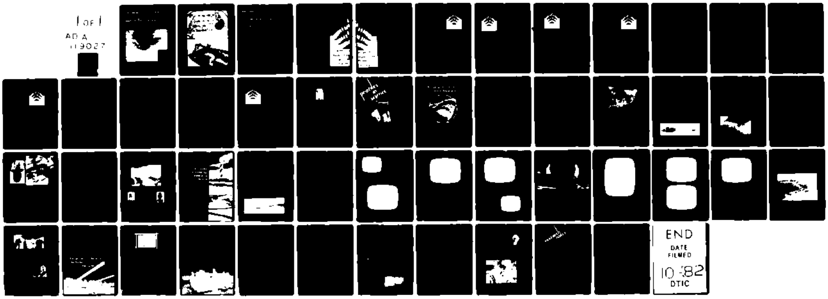

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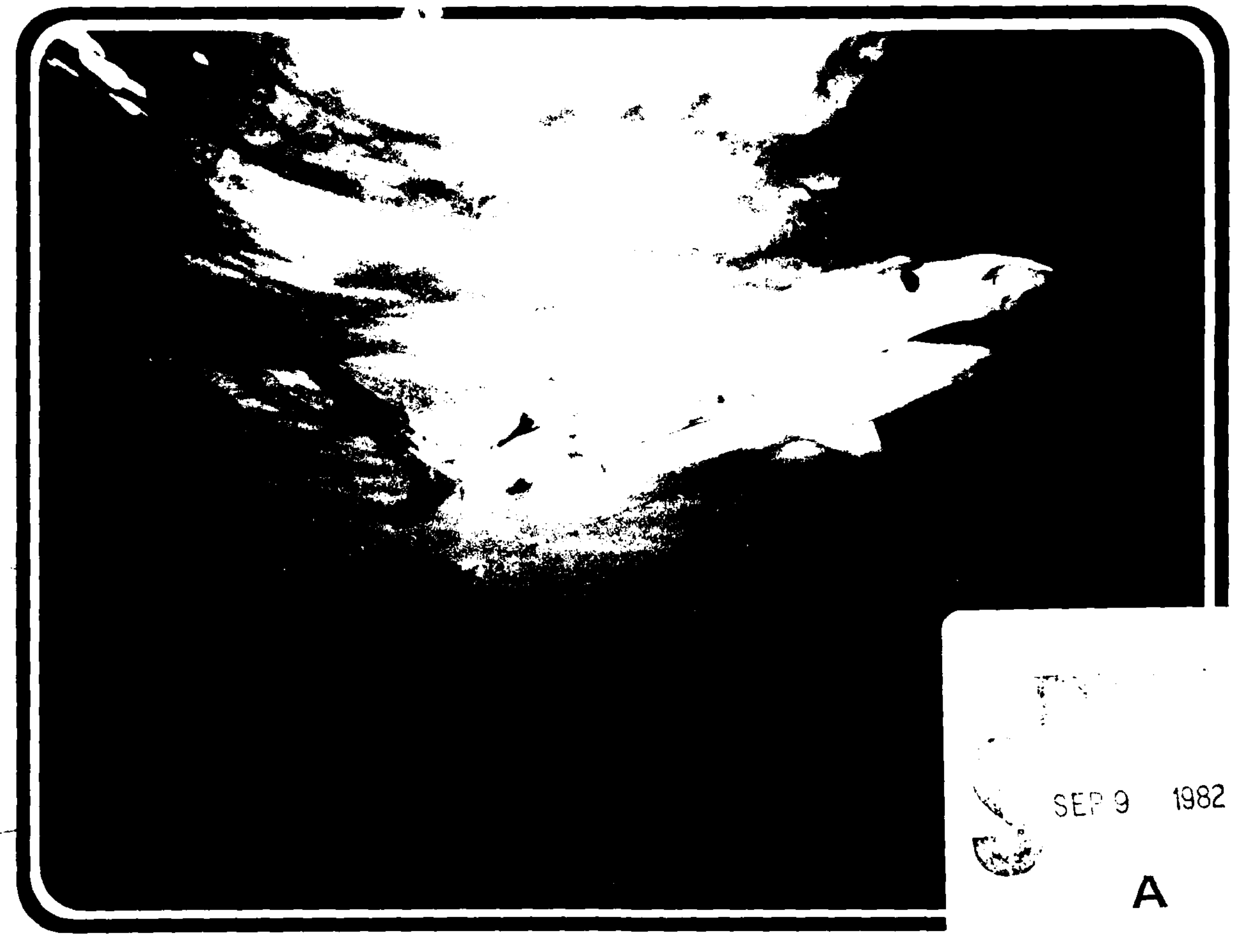
Naval Research Reviews



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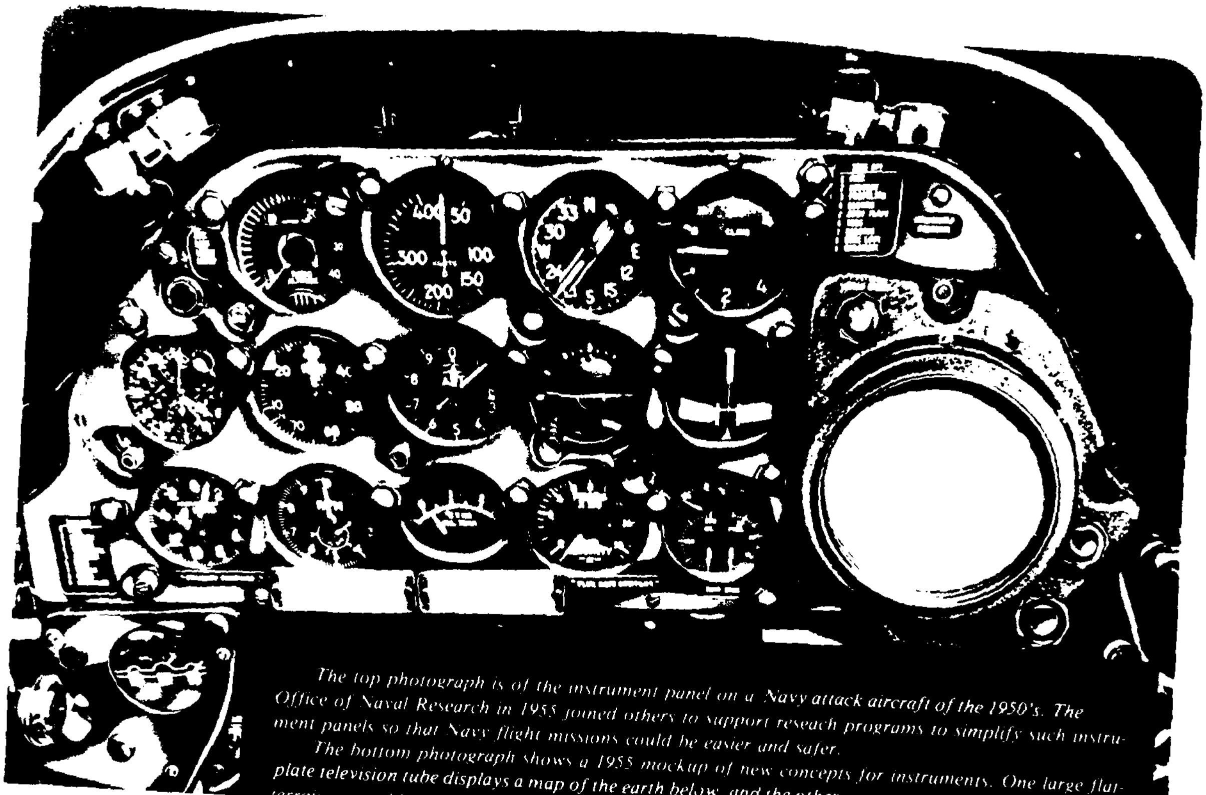

The top photograph is of the instrument panel on a Navy attack aircraft of the 1950's. The Office of Naval Research in 1955 joined others to support reseach programs to simplify such instrument panels so that Navy flight missions could be easier and safer.

The bottom photograph shows a 1955 mockup of new concepts for instruments. One large flat-plate television tube displays a map of the earth below, and the other represents the contour of the terrain into which the pilot is flying. The early reseach of ONR eventually proved successful. Today visual displays of moving maps and contour representations for terrain avoidance are frequently employed.

ONR continues to support reseach in the field of human engineering to help people perform more effectively with the ever increasing demands of new equipment and instrumentation.

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ARTICLES

DEPARTMENTS

About Our Cover

A black tip shark (Carcharhinus limbatus) 2.1 meters long is hooked with long line fishing gear at Walker's Key in the Bahamas. The line can be seen in the background. The shark was pulled to the research vessel, tagged, and released. The shark is tagged in order to study migration habits and growth rate. The photograph appears through the courtesy of Jim Kowalski.

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Researchers in artificial intelligence (AI) face the challenge of developing computer systems that can significantly augment the decision making capabilities and physical capabilities of human beings. The complex problems inherent in this task have attracted the interest of computer scientists, mathematicians, and psychologists. On the one hand, these scientists are seeking insights into the problem-solving techniques of human beings in order to find clues to the principles that should govern the design of "intelligent" automated systems, and on the other hand they are seeking to utilize advances in computer technology that offer alternatives to the mimicry of human thought processes.

The Information Sciences Division of the Office of Naval Research (ONR) has, in its support of basic research in artificial intelligence, served to focus the attention of scientists on the key research issues that are crucial to the development of technology with high potential for military applications. It should be noted, however, that much of the work to date has been of such a fundamental nature that it will likely benefit the offices and factories of future non-military environments as well. In particular, substantial progress has been made in the areas of:

a. Expert Systems, that provide problem-solving assistance in particular knowledge domains such as medicine, chemistry, and electronics.

b. Natural Language Understanding, that provides techniques for automating the understanding of speech, text, drawings, photographs, and movies.

c. Crisis Alerting Systems, that monitor large, complex, and perhaps geographically distributed databases in order to warn about impending crises.

d. Planning Systems, that can proceed from a very high level statement of goals to automatically generate detailed and optimal schedules, logistics movements, contingency plans, etc.

e. Situation Assessment, that requires the efficient integration of knowledge from many sources, some of which may be unreliable or contradictory.

f. Robotics, that addresses the requirements for smart machines capable of coping with unpredictable situations and of working in hostile environments.

A recurring problem in these research efforts is how to automate knowledge acquisition, i.e., the learning process. The problem arises, for example, in the design of expert systems that require the assimilation and organization of tremendous quantities of factual information, and also in the design of robotic devices that need not be dependent upon human tutors. The relationship between the processes of problem solving, scientific discovery, and learning was discussed by Dr. Herbert A. Simon in a talk that initiated a recent seminar series in Artificial Intelligence sponsored by the Chief of Naval Research. The paper below was the basis for that talk. The program BACON to which Dr. Simon refers is currently being revised and extended by himself and Dr.

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Patrick W. Langley under an ONR contract; one benefit of this work will be the development of new techniques for analyzing numerical data by forging a unique synthesis of statistical techniques with heuristic search methods. Dr. Simon was recipient of the Nobel Prize in Economic Sciences in 1978.

Dr. Alan L. Meyrowitz
Office of Naval Research

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tegies in The
Models of
Discovery

by
Herbert A. Simon
Carnegie-Mellon University

Introduction

Some recent artificial intelligence programs whose task is to simulate the processes of scientific discovery can be taken as models of the history and processes of discovery within the AI discipline itself. Consistently with these models, AI research relies basically on the methods of heuristic best-first search. Because of its necessarily vague and open goals, it works forward inductively (rather than backward in means-ends fashion), guided by a crude evaluation function that tests running programs to identify promising directions.

AI research is empirical and pragmatic, typically working with examples rather than theorems, and exemplifying the heuristic of learning by doing. In its essential reliance on weak methods and experiment instead of proof, it is adapted to the exploration of poorly structured task domains, showing considerable contrast in this respect to operations research or numerical analysis, which thrive best in domains possessing strong formal structure.

At scientific meetings it is customary to schedule, in addition to papers reporting specific pieces of research, "addresses," "keynote speeches," and the like, which may be described as meta-papers. The task of meta-papers is not to report research but to interpret the past and to peer into the future of the discipline. This is such a meta-paper. Presumably you expect me to say where artificial intelligence has been and where it is going.

Clearly, this is not a task for human intelligence. Human-beings are notoriously incapable of reviewing history—especially history in which they have participated—without rationalizing outrageously to make the past conform to their picture of the present. And human forecasts of the future almost always reveal much more about the forecasters' hopes, fears, desires and dreads than they do about the shape of the world to come.

Early in the history of AI, in 1957, Allen Newell and I made some predictions that became rather notorious.[1] Skeptics and opponents of AI used them as evidence of the recklessness and irresponsibility of the advocates of AI. (Optimistic forecasts seem to attract such charges much more often than do doomsday forecasts.)

Of course our forecasts were neither reckless nor irresponsible. As we said at the time, they represented our attempt to define in concrete terms the nature of the revolution in human affairs that was going to be produced by computers in general and artificial intelligence in particular. As scientists privileged to witness the early stages of a momentous development, we felt a responsibility to interpret that development to laymen, and the predictions were our interpretation. Nor was our forecasting seriously inaccurate, if one allows a time-stretch factor of two or three—a not unreasonable margin of inaccuracy in such crystal-ball ventures.

I cite this little piece of history not to defend my record as either a seer or a historian, but as empirical evidence for my doubts, expressed earlier, that either foresight or hindsight are fit tasks for human intelligence. Such doubts undermine the very foundations of meta-papers, including this one.

If human intelligence is unequal to the needs of history and prophecy, perhaps we should call on artificial intelligence. Perhaps we should ask what AI has to say about the processes of discovery. After all, we do have, today, a number of artificial intelligence programs that are capable of making discoveries of one kind or another—I have in mind particularly Douglas Lenat's Am program, and Patrick Langley's BACON. Perhaps these programs can tell us more about the research process than human beings can.

An AI program that makes genuine discoveries, or one that solves difficult problems, provides us with a theory of the discovery process, indeed, a theory in the most concrete and explicit form that is conceivable. Since these programs reveal to us some of the essential requisites and structure of the discovery process, we can use them to illuminate the history of discovery in the domain of artificial intelligence itself, and to provide some insight into the ways in which we can best proceed in future research and development aimed at new discoveries in that field.

This is the path I propose to pursue in this paper. First, I will summarize what seem to me some of the salient characteristics of successful artificial intelligence problem-solving systems, especially those

whose basic task is to make discoveries. Next, I will ask whether this list of program characteristics suggests why the process of discovery in the AI field itself has taken the particular course that it has. Finally, I will turn to the future, and ask what lessons we might learn from this experience in our continuing efforts to extend the boundaries of AI, particularly in the directions of greater capabilities for discovery and for solving ill-structured problems. If this route seems somewhat circular—AI illuminating itself—I remind you that circles may be either vicious or virtuous, and I will argue that this is one of the virtuous kind.

I will not try to cover every aspect of AI, and will undoubtedly overemphasize problem-solving and heuristic search at the expense of such areas as visual pattern recognition. This lapse will be the less serious to the extent that the techniques of heuristic search are today invading the domain of pattern recognition, bringing about a greater degree of unity in outlook throughout the whole field of artificial intelligence. So I will take, as Allen Newell and I did in our Turing Lecture, heuristic search as the central paradigm for artificial intelligence.[2]

AI Programs as Theories of Discovery

By a discovery program I mean a computer program whose output is not inferable in any obvious way from its input. The phrase, "in any obvious way," is essential to the definition, since we know that a program does exactly what we program it to do—which is usually not at all the same as doing what we supposed we had programmed *it* to do.

The Nature of Discovery

Novelty, in computers as in human beings, lies in the eye of the beholder. The result is novel if it was not expected from the outset. But even this definition is ambiguous. As the numerous documented cases of independent invention attest, a discovery may be novel to the discoverer but not to the whole society, for others may already have found it. However, to produce a novelty a second time, without knowledge that it has already been discovered by others, presumably requires the same kinds of cognitive processes as were required to produce it the first time. Anything we can learn by examining the program of the original discoverer we should be able to learn also by examining the program of the reinventer.*

It is probably true today that within any one hour period some computer program somewhere in the world has followed a path never before traversed, to produce a novel successful result. This must occur for example, more than once in almost every game played by a hobbyist's minicomputer chess program, since chess games rarely fully repeat others that have been played in the world. However, we generally do not apply the term "discovery" to every novelty of this kind, however rational or adaptive the output may be. We require, in addition, that the novelty be in some sense remarkable or socially valuable. In particular, and borrowing language from the patent law, to be an invention, a novelty must not be "obvious to a person skilled in the art." While a minicomputer playing Class D chess discovers many novel solutions to its problems, these solutions would presumably be discovered easily by strong players, hence would not qualify as inventions in the legal sense.

Even today, after a quarter century of AI efforts, it is hard to point to fully convincing examples of discoveries by artificial intelligence programs that satisfy this stricter definition, of being neither rediscoveries nor obvious to one skilled in the art. If pressed on this point, I might want to defend certain products of chess programs, programs for musical composition and visual design, and theorem-proving programs as meeting the stricter requirements of invention, but such a defense would take me away from my main concern here.

I will draw my examples of discovery from computer programs that have mainly rediscovered what was already known, but whose discoveries are hardly trivial, and would indeed have been adjudged important if they had been genuinely new. I have in mind such examples as the discovery by Lenat's AM program of the concept of prime number and its conjecturing of the fundamental theorem of arithmetic—that every positive integer can be represented uniquely as a product of powers of primes.[3] Examples of a slightly different kind are BACON's induction from empirical data of Kepler's Third Law, Ohm's Law, and the Laws of Boyle and Charles.[4]

** This claim requires some qualifications. The reinventor may possess knowledge—not the invention itself, but knowledge relevant to it—that was not available to the original inventor, but which makes the job easier the second time. Later, I will have more to say on this point as it applies specifically to AI.*

Before we take the programs that found these concepts and laws as exhibiting the essential processes for discovery, we must satisfy ourselves on one point: that the human programmers did not, in some explicit or implicit way, embed the results at the outset in the programs and their inputs. Since we have already agreed that the outputs of programs are determined by the programs (and data), what can we mean by this requirement? Simply that the derivation of the outputs from program and data be sufficiently non-obvious. This is, of course, the same criterion we apply to a mathematical theorem to determine whether it is "deep"; and it is the same as the legal requirement for invention, quoted above.

This is not to say that it is a precise criterion, statable in a formal way. The only way I know to decide whether AM or BACON, or any other program purporting to have powers of discovery (but exhibiting those powers through rediscovery) genuinely possesses such capabilities is to search the code carefully for hideaways where the conclusions may be concealed in the premises. The severity of the test will depend on how thoroughly the search is made and how strict a criterion of obviousness is applied. Since I know of no way at the present time to quantify either of these two dimensions of the test, we must still depend (as we do in evaluating the merit of scientific discoveries) on informal judgement.

From close familiarity with the AM and BACON programs, I am satisfied that these two programs pass any reasonable tests of this kind. Let me, then, comment on the structure of the programs—on the sources of their powers of discovery. For the sake of those of you who are not acquainted with AM or BACON, I will first state briefly what each program does. As already noted, a fuller description of AM, by Doug Lenat, will be found in the Proceedings of the Fifth International Joint Conference on Artificial Intelligence,[3] and of BACON, by Pat Langley, in the Proceedings of this conference.

Lenat's AM Program

AM is a system that discovers new concepts and that conjectures new relations among them. Its input consists of an initial stock of concepts (in one application, the basic notions of set theory), goals and criteria (the goal of discovering new concepts and possible relations among concepts, and criteria for evaluating the worth or interest of concepts), and heuristics for searching for new concepts. Among the criteria for judging if a concept is interesting is how closely it is related to other interesting concepts, and whether examples of it can be constructed—not too easily, but with not too much difficulty. The search heuristics include the advice to construct examples, to pay particular attention to borderline examples, to particularize when examples are found too easily, to generalize when they are hard to find. This is the kind of initial information available to AM—initial concepts, goals and criteria, and search heuristics.

The control structure of AM guides it in a best-first search; the criteria of concept worth determine which of the concepts already attained should be the starting point for the next quantum of search. On its most celebrated run, starting with the concepts of set theory, AM discovered— among other things—the integers, the arithmetic operations of addition, subtraction, multiplication and division, the concept of prime number, and, as I mentioned earlier, the prime number representation theorem. When it began concerning itself with numbers possessing maximal (instead of minimal) numbers of prime factors, Lenat thought it had entered on truly new ground, only to find that this territory had earlier been explored by the self-taught Indian mathematician, Srinivasa Ramanujan. Therefore, AM must be evaluated as a rediscover, rather than a discoverer of new mathematical truths.

Langley's BACON Program

BACON is a program that induces general laws from empirical data. Given sets of observations on two or more variables, BACON searches for functional relations among the variables. Again, it carries out a form of best-first search, in which a criterion of "simple things before complex" guides what to try next.

BACON's search is highly selective; it does not try all possibilities. It arranges the observations monotonically according to the values of one of the variables. Then it determines whether the values of some other variables follow the same (or the inverse) ordering. Picking one of these other variables, it searches for an invariant by considering the ratio (respectively product) of this variable with the original one. If the ratio (product) is not constant, it is introduced as a new variable, and the process continues. Thus, the newly defined variables in BACON correspond to the new concepts in AM, and the process is driven by a search for invariants.

It is easy to see how BACON, discovering that the product of electrical current by resistance in an electrical circuit was constant, would be led to Ohm's Law. The case of Kepler's Third Law requires BACON to generate, successively, ratios of powers of the radii of the planets orbits to powers of their periods of revolution, arriving at the invariant, D^3/P^2, after a search of a small number of possibilities.

I have mentioned only a few of the salient features of BACON. The system has at least crude means for ignoring noise as data, and a number of other interesting features, but I will leave their fuller description to the program's author. What is interesting for our purposes is that a program, equipped and organized as I have described, detects regularities in data sufficiently perceptively to rediscover important scientific laws.

AM and BACON use similar schemes of memory organization. The ability to apply the same basic processes to given information and to newly generated concepts or variables, respectively, hence to operate recursively, is guaranteed by using a homogeneous format for the storage of all data. Though the details of the data structures are different for the two programs, both use schemas—structures of property lists—to describe the objects with which they deal or which they generate. The main element of rigidity in their memory organizations is that the specific properties that may occur in these schemas—the "slots"—are specified in advance and known to the programs.

Discovery Mechanisms

The theory of discovery that emerges from an examination of how these programs work contains little that should surprise us—unless we have been seduced by the often-repeated myth that discovery processes, being "creative," somehow stand apart from the other actions of the human mind. In AM and BACON we see discoveries being produced by precisely the same kinds of symbolic processes that account for the efficacy of other AI problem-solving programs: theorem provers, chess players, puzzle solvers, diagnosis systems. A space of possible concepts and relations (AM), or of possible invariants (BACON) is searched in a highly selective, best-first manner. The search mainly works forward inductively from the given concepts or data.

The discovery programs are distinguished from most other problem-solving systems in the "vagueness" of the tasks presented to them and of the heuristic criteria that guide the search and account for its selectivity. Because the goals are very general ("find an interesting concept or relation," "find an invariant"), the use of means-ends analysis to work backward from a desired result is not very common. By and large, the programs work forward inductively from the givens of the problem and from the new concepts and variables generated from these givens.

Both programs work at a very concrete level. AM makes a major use of examples, which it is capable of generating, in searching for new concepts. BACON works with numerical data. If we observed human scientists working in the manner of these programs, we would regard them as very pragmatic. We are reminded of Faraday's notebooks, in which he recorded, day after day, the experiments that were suggested to a curious mind by the findings of the previous day's experiment. Or, we think of Mendeleev arranging and rearranging his lists of the elements until their periodic structure begins to emerge from his worksheets.

Both programs discover, they do not prove. Their task is to find regularity and pattern in nature, not to demonstrate the necessity of that pattern. Although their heuristics appear very general and weak—they do not rely at all on semantic information about the task domain that is being explored—they accomplish the search tasks with a remarkably small amount of trial and error. In the best tradition of heuristic schemes, they operate without any guarantees that they will succeed, but they do succeed in finding many interesting results. We would not even know how to define completeness for programs given these kinds of ill-defined tasks.

Because the tasks addressed by these systems are poorly defined, we do not have good measures of how powerful they are. Of course, we can make our personal evaluations of the quality of their discoveries—of how impressed we are that AM finds the prime number factorization theorem, or that BACON readily induces Ohm's Law from the data. But we do not have the precision of comparison with human performance that a chess program gives us, or a program for medical diagnosis. The difficulty of evaluating them is compounded by the absence of a yardstick for measuring the knowledge with which they are endowed at the outset, or that is embedded in the program structures. We do not know whether BACON had the same starting point as Ohm, or whether one of them was faced with an essentially simpler problem of induction than the other. Of course the same uncertainities surround all of our attempts to evaluate human discovery also. AM and BACON pose no new methodological puzzles in this respect.

How does the behavior of these programs compare with the behavior of the human scientists who have labored in the vineyards of artificial intelligence during the past 25 years? Do AM and BACON provide a true, if rough and approximate, description of that discovery effort? And what of the future of AI? Can these discovery programs help us in either prediction or strategy? Let me turn first to the history.

The Discovery Process in AI

Artificial intelligence has sometimes been criticized as being atheoretical, and consequently as having no solid substance. Of course, the premise might be true but the consequent false, unless we believe that all truth takes the form of rigorously proved theorems. Artifical intelligence has certainly been short of theorems, and in a field as densely populated with mathematicians and former mathematicians as is computer science, its nakedness in this respect has not gone unnoticed.

It may be objected that I am neglecting the A‡ algorithm, or the various interesting properties of Alpha-Beta search, or even the theorems that Kadane and I have proved about optimal evaluation functions for best-first all-or-none search.[5] But these isolated examples, even if we add to them all the other known to us, do not constitute a theory of artificial intelligence. At best, they provide us with some islands of theory, separated by wide expanses of an atheoretical ocean. Moreover, the heuristics of best-first search implied by these examples were known empirically and used in running AI programs for many years before the mathematics was developed.**[6]

AI as Empirical Inquiry

I am afraid that we must resign ourselves to the fact (or celebrate it, depending on our taste in science) that artificial intelligence has not been a

***The Logic Theory Machine, in 1958, already incorporated best-first heuristic search, while the Alpha-Beta heuristic is to be found in chess programs as early as 1958.*

branch of mathematics, but rather a field of inductive, empirical inquiry. The main strategy of investigation has been to propose tasks requiring intelligence for their performance, to write programs for handling those tasks, and to test the efficacy and efficiency of the programs by giving them a sample of tasks drawn from the domain in question. Nearly everything we have learned about artificial intelligence over the past 25 years (and much of what we have learned about human intelligence as well), has been found by following this experimental strategy. And the body of knowledge that exists in AI today is better described as a store of experimental data and inferences drawn from them than as a collection of mathematical truths.

But the process I am describing corresponds closely to the kind of process that is carried out by AM and BACON. We have seen that both programs are inductive and experimental—even if the product of the former's efforts are mathematical constructs and conjectures, and of the latter's, postulated functional relations among numerical variables. Neither AM or BACON proves anything. If they produce conviction, it is the conviction of the empirical scientist, relying on some postulate of the uniformity of nature, rather than the conviction of the mathematician, relying on the certainty of the laws of logic.

Inferring Principles From Programs

The problem-solving tasks that AI research has addressed during the past 25 years, like the tasks addressed by AM and BACON, seem largely fortuitous—targets of opportunity: theorem-proving in logic and group theory, the Eights Puzzle and Missionaries & Cannibals, chess, Euclidean geometry, medical diagnosis, mass spectrogram analysis, speech recognition, parsing natural language, to mention a few. An assiduous historian could no doubt track down the reasons why each of these domains was attempted, but those reasons would not add up to a grand strategy for artificial intelligence. Probably the choice was neither much more nor much less considered than the choice of sweet peas and fruit as favored organisms for genetic research.

The true comparison is between these tasks, on the one hand, and the examples generated by AM or the data sets of BACON, on the other. The central inductive problem for AI has been to generalize from the performance of programs dedicated to individual tasks some principles (empirical principles, not necessarily theorems) about the mechansims required for intelligent problem-solving behavior. How successfully this problem has been solved can be judged by assessing how far new AI programs make use of the heuristics and structural principles of the programs already in existence, and by examining the extent to which AI textbooks are organized in terms of general principles.

On both scores there is evidence of steady progress in AI. In the first decade or two, one can find a number of reinventions of general principles by investigators who were exploring different task domains (or even, occasionally, the same task domain). For example, best-first search apparently appeared initially, as already noted, as a component of one version of The Logic Theory Machine, disappeared in early versions of GPS, which tended to be oriented towarded depth-first search, and reappeared in the MATER chess combinations program.[7] As another example, schemas appear in programs as early as 1956, but were subsequently reinvented and rechristened "templates" or "frames"[8]. During the past five or ten years, however, the main structural components of AI programs have been identified, and a reasonably consistent vocabulary adopted for referring to them.

This gradual progress toward awareness of general principles is reflected by the textbooks in the field. Early textbooks were little more than collections of examples of more or less successful problem-solving programs. Beginning with Nilsson's book, *Problem-solving Methods in Artificial Intelligence*[9], some general threads of organization began to appear, and specific programs were not merely described, but were analyzed for their contributions to these threads. With all this progress, the contemporary books still reflect the pragmatic and empirical foundations of the field, and resemble textbooks in geology more than they resumble treatises in analytical mechanics.

Departures from the Discovery Model

There is one respect in which the history of AI research departs significantly from the trace of a computer discovery program, for in the AI world, many lines of inquiry can be pursued simultaneously—provided that the discipline is sufficiently well populated by researchers, and that the researchers are not too much driven by fads. Hence, when we try to interpret the annals as exemplifying best-first search, we must use that term loosely. To be sure, there was a period of several years during which attempts at theorem-proving nearly dominated AI research, and a more recent period when much of the inquiry was focused on problem-solving in knowledge-rich domains. When a topic like one of these seems to be progressing rapidly, it attracts much of the field's research effort, as would be true of a best-first search system. But other lines of investigation are never wholly dormant.

What has happened when the AI research strategy has departed from the discovery model? The most instructive examples are the cases where pragmatism was sacrificed to the demand for more theory and formal development. One such case is theorem-proving, where mathematical tests have exercised greater influence than in most other AI task domains.

From the time of Haw Wang's early and successful program for proving theorems in the propositional calculus,[10] most theorem-proving efforts have placed great emphasis on the completeness of their programs and upon employing elegant proof methods (e.g., natural deduction and resolution) from symbolic logic. Since completeness is most easily proved for breadth-first programs that do not use pragmatically constructed selective heuristics, the mainstream of research eschewed best-first search and heuristics that lacked guarantees of completeness.

When heuristics could be used that did not threaten completeness (e.g., set of support), they were adopted readily, but heuristics possessing this guarantee were not in sufficiently long supply to prevent the exponential explosion of search trees. The net result has been a general disillusionment with the progress of theorem-proving research, and diversion of effort to other task domains within AI. Some exceptions can be found, of course. For example, in the impressive work of Bledsoe and his associates, we see exhibited a much more pragmatic attitude towards heuristics than has been characteristic of theorem-proving research in general.[11]

AI as a Residual Domain

Some years ago, Allen Newell described artificial intelligence as the domain of weak methods, a description that still seems to hold.[12] This is not because anyone prefers weak methods to strong. No one would solve a problem by heuristic search if he thought that the simplex algorithm of linear programming would do the job. But strong methods apply only in domains that have sufficiently rich and smooth structure to support them. The simplex method works only in a problem space that is convex, bounded by linear inequalities, and with a linear criterion function to be maximized. The method exploits the mathematical structure of the space to home in on solutions in a relatively direct and straight forward fashion.

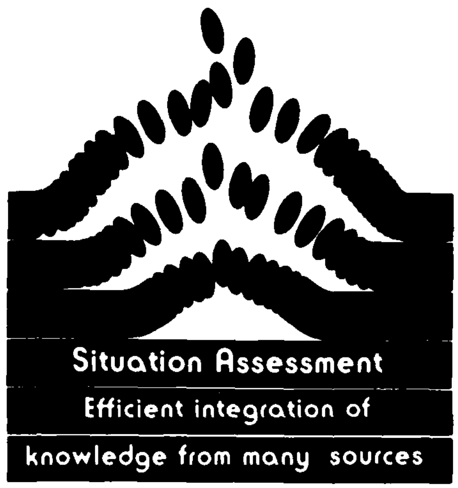
AM, and to a lesser extent BACON, are designed to work in spaces that have little regular structure, or which have structure that is initially unknown to the program. They use the weak methods of heuristic search for the same reason that artificial intelligence has used those methods—because not enough was known, in advance, of the shape of the problem space for stronger methods to be used.

Similarly, attempts to derive measures of computational complexity for typical AI domains have not yet yielded much of a mathematical harvest. Proofs about the dependence of amount of computation, in the worst or average cases, upon problem size depend on knowledge of structural features of the problem domain, and where such structural features are unknown or absent it becomes difficult to obtain strong mathematical results.

Necessity should not be redefined as a virtue. Yet, it makes some sense to define artificial intelligence as a residual domain—the domain in which it has not yet been possible to substitute powerful special-purpose techniques for weak methods. At any time that such techniques are discovered for a particular subset of problems, those problems are removed from the jurisdiction of AI to that of operations research or numerical analysis. But human intelligence, applied, for instance to the discovery of new knowledge, is not limited to working in orderly domains that have strong structure, and it is the task of AI to show how intelligence works, and even to complement its working, in less well structured domains.

From Past to Future

If we take AM and BACON as our models of the discovery process, then we should despair of making exact forecasts of where artificial intelligence research is likely to go in the next few years. For the discovery process illustrated by those programs is myopic, its best-first search responding to intimations of opportunity. Consequently, targets will continue to shift, as they have shifted in the past, to those task domains that exhibit from time to time, most promise of movement.



Allocation of Effort

One important difference has already been noted between a discovery process programmed for a serial digital computer and the social discovery process of the AI community. That community is a parallel, rather than a serial, machine. With the increase in manpower that has been attracted to the field in the past five years, the prospects are now brighter than they were earlier for maintaining sustained research activity in a number of AI domains at the same time. At the present time, for example, a more or less continuous effort of several research groups is being devoted to chess programs, to natural language understanding, to visual pattern recognition, to medical diagnosis, and to various kinds of information retrieval tasks.

The fact that a computing system has modest parallel capacity does not, however, invalidate the main features of the best-first search model. The parallel capacity is still highly limited, and does not grow exponentially (at least not for long), as it would have to in order to avoid decisions about what part of the tree to search next. The effort allocation problem for a parallel, but not exponentially growing, system is merely a little less poignant than the problem for a strictly serial system. At any given moment, several branches that are most promising for exploration have to be chosen, instead of a single branch. Hence, with limits of both manpower and funding in AI, increased activity in some directions means decreased activity in others.

For example, research on speech recognition appears to have receded again to a relatively low level of activity with the termination of the special Advanced Research Projects Agency funding, as has AI research on robotry. (I will have a bit more to say about robotry research later, but will simply observe now that the current boom in industrial robotry is only tenously connected with the main stream of AI research, and makes only limited use of AI methods.) Automatic programming has never reached the level of attention that its potential importance and centrality to AI would seem to justify. Theorem-proving—and problem-solving in general—appear to be attracting relatively little effort currently.

Judged in terms of the contents of the Proceedings of the 5th International Joint Conference on Artificial Intelligence, natural language is attracting the most attention in AI research, followed closely by vision and the representation and acquisition of knowledge. These three areas together accounted for about 60% of all the papers.

The Evaluation Function

From the shifts in allocation of research effort, we can draw some conclusions about the evaluation function that is used to guide the best-first search. But we must note carefully whose evaluation function it is. To those of us who have been working in AI, it is obvious that the shifts in emphasis among speech recognition, robotry, and automatic programming (these especially, but not exclusively) have been determined to a much greater degree by the judgments of funding agencies as to what kinds of work were more likely to lead promptly to practical application, than by the judgments of the researchers as to what lines of inquiry held the greatest promise for advancing fundamental knowledge.

In part, this vulnerability of the research agenda to genuine or imagined priorities for applications is the price that AI pays for being a "big science" field, dependent for its progress on the availability of expensive computing equipment. But some other big science fields—for example, radio astronomy—have attained considerable freedom in selecting their research goals, and we can only hope that AI can gradually acquire similar autonomy as the field becomes better established and the fundamental character of the phenomena it studies more widely understood.

If I were to contrast my own personal evaluation function with the function inferred from the actual present allocation of effort, I would be inclined to give considerably more attention to the domains of robotry (that is, the AI aspects of robotry) and automatic programming than these areas are now receiving. Later, I will have a few words to say about the reasons for my preferences.

Common Themes

One factor that mitigates the possible damage done by the whims of funding agencies and the fads of AI research itself, is that there is a considerable overlap in the basic problems encountered, and in the basic AI mechanisms required to solve those problems in all the task domains where AI research is carried on. Best-first search, for example, is a recurring theme, regardless of whether we are concerned with theorem-proving, chess playing, or robot planning. Similar problems of data representation, organization, and access must be faced in almost all task domains. Many tasks call for natural language capabilities of wider or narrower extent. The context-dependence of knowledge acquired through search, and the extrapolation of knowledge from one context to another is a recurrent theme. Because of these commonalities, progress in our understanding of any new task is likely to contribute substantially to progress for other, temporarily dormant tasks.

But these benefits of commonality will be realized only if we pay explicit attention to the transfer problem. The existence of multiple parallel research efforts in different tasks domains increases the danger that the same principles and mechanisms will be reinvented, perhaps more than once, by specialized investigators who are unaware of work going on outside their own narrow areas. As the AI research field grows and more investigators enter it, specialization will undoubtedly grow also (it has already), and the dangers of duplication will increase correspondingly.

Perhaps the most important preventive step against reinventing wheels is to define research goals not simply in terms of constructing programs that will perform specific tasks well, but in terms of using programs as examples and test beds for generating and illuminating general principles. Computer science has its roots in both scientific and engineering traditions. For the engineer—at least the nonacademic engineer—the device is the thing; the proof of *his* pudding is in how well the system he has designed works. For the computer scientist, the device (the program) is not an end in itself, but a means for testing whether particular methods and principles, incorporated in the device, perform the functions for which they are intended. Journal referees and reviewers of funding proposals can contribute much to the development of AI by insisting on these broader goal specifications for AI research projects.

There would also appear to be room in AI research for more generalists and theorists who would devote their attention to extracting general principles by comparative analysis of programs in different task domains. Of course such activity goes on at the present time, but perhaps it would be encouraged further if we did not restrict the term "theory" to formal, mathematical developments.

It might appear that I have fallen into a contradiction. Using AM and BACON as my models of discovery programs, I pointed out the futility of trying to predict the course of discovery. Now, only a few paragraphs later, I am expressing my views about the allocation of effort. There is, in fact, no contradiction. In best-first search, choosing an evaluation function and using it to guide the allocation of effort is unavoidable. This does not mean that one can predict where the search will lead; but a well-chosen evaluation function can indicate the most productive points at which it can start. Let me offer a few illustrations.

Research on Robots

One criterion of a promising task domain is that successful AI programs in the domain will rely on important components of intelligence that have not been much explored in other research. Robotry is a promising domain, because it takes us away from planning actions in simple worlds of the imagination—where the consequences of our actions can be deduced precisely—into planning actions in complex real worlds, where we must be prepared to readjust our estimates of the state of the world repeatedly as our actions fall short of or beside our intentions.

Methods for matching the predicted to the actual state of the world, and for correcting the former to reflect the latter, are fundamental to the success of systems that can survive in complex environments and particularly in environments where there is much uncertainty.

When I refer to robotry research, I have in mind something rather different from the development of industrial robots that is now burgeoning in a number of countries. Most industrial robots are being designed to carry out fairly restricted ranges of tasks in factory environments that are carefully tailored to the robots. Moreover, AI techniques have not played a prominent role in these developments, most of which come out of the tradition of engineering control theory.

In this application, the residual status of AI methods is again apparent. If an environment can be sufficiently smoothed and simplified, then the methods of servomechanism and control theory may provide the best means for designing flexible devices to operate in that environment. AI methods are likely to have a comparative advantage in rough and complex environments that have to be dealt with in their raw natural form. For this reason, research on vehicles capable of locomoting autonomously on remote planets is probably more relevant to basic issues in artificial intelligence than is research on industrial robots that are to operate in factory environments. The former kinds of systems will have to be flexibly intelligent to a much higher degree than the latter.

However, I do not want to overstate the case. As the development of industrial robots goes forward, there is a need for strong capabilities in visual pattern recognition, a domain in which artificial intelligence concepts are likely to play a role of increasing prominence. The point of my example is that we don't simply want to sieze on robotry as a task domain, but want to ask what aspects of robotry call especially for AI approaches, and what light is likely to be cast on general AI concerns by research focused on those aspects.

Automatic Programming

A second domain I singled out as promising for AI research today is automatic programming. Here again, the general value of the research for advancing our basic understanding of artificial intelligence depends on how the problem is defined. I have especially in mind systems that would take ill-structured and incomplete descriptions of a desired program (of the sort we would give as instructions to a human programmer), and transfer them into executable code. Automatic programming, so defined, is an excellent domain in which to experiment with the automatic design of problem representations—a problem we must address if we are to extend AI further into ill-structured domains.

An additional reason why automatic programming tasks deserve high priority on the research agenda is that they offer excellent opportunities for work on natural language and knowledge representation. Research in the latter two fields has sometimes suffered from vagueness in the specification of the task. To study natural language effectively we must study particular kinds of situations in which information and meanings have to be communicated for a definite purpose. The automatic programming task defines that purpose (as does also the closely related task of understanding problem instructions written in natural language). By the same token, we are apt to learn most effectively about the problems of knowledge representation in the context of a specific task domain like automatic programming.

If we accept necessity as the mother of invention, we must remember that another parent is needed too. Automatic programming deserves a high rating for its research potential only if there is reason to believe it can be done—that our basic knowledge has reached the point where it is reasonable to talk about automatic design of task representation. I would argue that both the progress—modest though it be—that has already been made in automatic programming, and the progress in the design of representations for other domains provide favorable indications that we ae ready for the next step.[13]

Local and Global Knowledge

A problem that has plagued heuristic search systems from the beginning is that information gathered at one node in a search through a problem space is not generally usable by the system to guide its search in other parts of the space. The same information may have to be generated again and again at different nodes.

Partly, this is a problem of information organization, solvable through such devices as blackboard schemes.[14] In such schemes, information is not stored in association with the nodes at which it is generated, but is placed in a common space where it becomes permanently available to all parts of the program, and at all times during the exploration of the problem space.

But there is a deeper problem with making information more broadly available: the information may be true only in a local context. Then the boundaries of this context must be determined and associated with the information before it can be exported safely. There is still not much theory (or experience) in the AI literature as to how this is to be done, but some progress has been made toward solving the problem in connection with research on speech recognition programs and chess programs, both of which are promising environments in which to pursue this issue.[14]

Learning Systems

In AI a great deal more progress has been made in constructing performance programs than in designing programs that learn. In the early history of artificial intelligence, the topic of self-organizing systems was pursued vigorously but, as it turned out, not particularly successfully. As the best-first search progressed, the nodes associated with this topic received low evaluations, and were gradually abandoned.

Yet the topic of learning in AI is not at all dead; rather it has been redefined. In early efforts, great importance was attached to starting systems off at or near ground level. The guarantee that they were learning was that they started off knowing almost nothing. Today, we characterize learning in a somewhat different way; we look for adaptive change, and we look for that change to be recursive and cumulative.

In the broadest sense, any program is a learning program that gradually changes over time so that on each new encounter with a particular kind of task it behaves in a more appropriate way. In neither human beings nor computers should we expect to find just a very limited number of processes called "learning processes," for there generally are a multitude of ways in which a complex system can modify itself adaptively.

Learning will generally be incremental. That is, each new step in adaptation will itself improve the capacity for further adaptation. A problem-solving system becomes a learning system whenever it is designed so that problem solutions can be stored and used to contribute to subsequent problem-solving. Clearly, discovery programs like AM and BACON are learning programs, since their explicit task is to produce novel outputs and to use those outputs recursively.

With this broader definition of learning, a whole spectrum of AI systems qualify as learning systems. Learning can connote all degrees of passivity or activity of the learner. Thus, at one extreme, we have interactive systems aimed at making it easier for the programmer to add new knowledge to an information structure, where the program itself is a wholly passive learner. At the other extreme, we have adaptive production systems that are able to extract information from their experiences, and use the information to improve themselves even without explicit instruction from outside. Most systems that learn from experience are aided, of course, if the experience is organized for them in a favorable way—in a succession of carefully graded lessons. It is the skill of a good teacher to present experience in this way.

One might ask whether it is time to revive learning as a major explicit goal of AI research. Since learning pervades almost all aspects of intelligent performance, the right search strategy is probably to incorporate learning goals in our performance systems. That seems to be a quite natural thing to do in building systems for visual pattern recognition, for example, for automatic programming, or for understanding natural language instructions.

But there are apprentices in the world as well as

journeymen; and presumably the apprentice's first concern is his learning rather than his performance. So pernaps there is room, on the tree of AI research, for an active branch that works with tasks in which learning and adaptation are the central concerns. Considering the recent rapid progress that has been made in constructing adaptive production systems, good progress can be anticipated along that branch, and I would assign it a rather favorable evaluation. But the fact that some investigators specialize in learning processes should not deter the rest of us from experimenting with learning components in our *performance systems.*

Conclusion

In this paper I have reviewed the AI community as if it were a medium-size slightly parallel processor searching its way in inductive, best-first fashion through the problem space of intelligent action. I have compared it with some of the existing AI programs that best characterize the discovery process. The comparison does not yield any great surprises, but perhaps provides some reassurance.

As a typical example of a discovery program, the AI community uses weak methods under the guidance of a somewhat imprecise evaluation function and vague ultimate goals. It tries to discover the mechanisms that enable a system like the human mind to behave purposefully, adaptively, and sometimes even effectively over a wide range of difficult and ill-structured tasks.

The search is highly pragmatic, steered and redirected by concrete empirical evidence culled from experiments with programs operating in an accidentally determined collection of task environments. The output of the research is mostly encapsulated in heuristics, not yet formalized in coherent theories of broad scope. All is confusion and mild chaos, as it should be at an exciting frontier of fundamental scientific inquiry. Although only a quarter of a century old, the search has already yielded a solid body of empirical knowledge about the nature of intelligence and the means of capturing it in programs.■

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His books include Administrative Behavior, Human Problem Solving (with Allen Newell), *The New Science of Management Decision* (rev. ed.), *The Sciences of the Artificial,* and *Models of Thought.*

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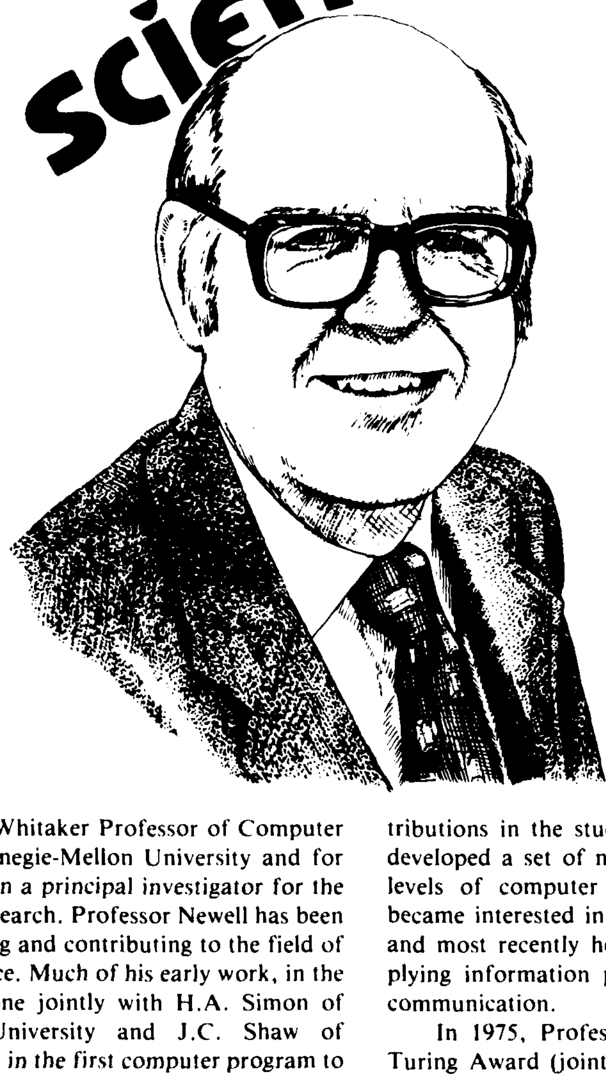
profiles in science



Allen Newell is Whitaker Professor of Computer Science at Carnegie-Mellon University and for many years has been a principal investigator for the Office of Naval Research. Professor Newell has been a pioneer in defining and contributing to the field of Artificial Intelligence. Much of his early work, in the mid-fifties, was done jointly with H.A. Simon of Carnegie-Mellon University and J.C. Shaw of RAND and resulted in the first computer program to prove theorems, the development of the technique of list processing, and the first program (GPS) to work on a range of problem solving tasks. In the mid-sixties, Professor Newell made important contributions in the study of computer structures and developed a set of notations for describing various levels of computer systems. In the seventies he became interested in speech understanding systems, and most recently he has been concerned with applying information processing psychology to user-communication.

In 1975, Professor Newell received the A.M. Turing Award (jointly with H.A. Simon) from the Association for Computing Machinery, and in 1980 he served as the first President of the American Association for Artificial Intelligence. ■

Bioassay of Surfactants as Shark Repellents

by

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Introduction

The search for a truly effective shark repellent continues. The need for repelling or at least controlling sharks is obvious: they interfere with the Navy's mission through attacks on both naval personnel and equipment. Anxiety created by sharks also interferes with naval operations. Therefore scientists continue to explore ways to control the behavior of sharks.

Past investigation on repellents *per se* has been done on a somewhat haphazard basis. A "shotgun" approach was used in hopes of stumbling upon an effective chemical substance. In parallel work, various devices were developed in an attempt to behaviorally disable or physically damage the shark. None of these efforts has produced an entirely satisfactory shark repellent. The failure of U.S. Navy "Shark Chaser" underscores this fact.[1]

While funding was available in the 1960's and early 1970's to systematically explore shark behavior and sensory physiology, research directed toward shark repellents has more recently shifted to the search for biologically effective natural marine products. During the processes of evolving anti-predator strategies, certain marine organisms may have already "invented" an effective shark repellent. To date, the most noteworthy of these protected forms is the moses sole (*Pardachirus marmoratus*[2]) with its toxin, pardaxin (PX). Navy-supported studies demonstrated that *P. marmoratus* produces a proteinaceous secretion that, in its most effective state can paralyze small white-tip sharks (*Triaenodon obesus*). In addition, Clark[3] demonstrated that teleost fishes, other than *P. marmoratus*, could be protected by covering their bodies with its crude secretion. Continuing studies showed that PX was composed of a complicated sequence of 162 amino acids[4], that it interfered with a host of biological systems[5] and that it affected fish gills[6] and ion transport systems of the dogfish shark (*Squalus acanthias*). Pardaxin looked promising indeed.

Two problems remained unresolved however. First, PX is difficult to obtain, practically impossible to synthesize and therefore very expensive. Secondly, its shelf life, in an aqueous solution, is extremely limited. In a freeze-dried form, however, it may be stored indefinitely, but the lyophilization process greatly reduces its potency. In addition, it is noteworthy that there was some disagreement concerning the precise mode of aciton of PX. One group (Primor and colleagues) claimed that PX specifically interfered with ion transport an osmoregulatory processes in fish gills. A second group (Zlotkin and colleagues) suggested a more generalized mode of action: due to its amphipathic and surfactant-like properties PX primarily interacts with membranal phospholipids and therefore affects a wide variety of physiological processes including the sodium pump of the fish gills.[7]

Progress in the search for a shark repellent from natural marine products was summarized in a symposium given at the January, 1981, annual meeting of the American Association for the Advancement of Science in Toronto. This symposium was convened by the Office of Naval Research to bring together scientists from different fields for a seminal exchange of ideas. It is from this meeting that the work reported herein arose.

As mentioned, Zlotkin hypothesized that the surfactant qualities of PX might underlie its repellency. If this be so, he further suggested that synthetic surfactants might also repel sharks. At the same meeting, Gruber outlined progress in behavioral studies of sharks and mentioned several different tests that could be developed to bioassay substances rapidly and reliably for shark repellency. Thus, we combined ideas and ultimately techniques in an effort to produce the results given below.

We will show that Zlotkin's prediction was correct; namely, that inexpensive synthetic surfactants do repel sharks. We will further show that the trance-like state of tonic immobility provides a rapid and apparently reliable behavioral bioassay for repellency; and that the lemon shark is an excellent subject for such studies. Thus a theoretical framework within which the search for a repellent can proceed and bioassays using live sharks for that search have been developed.

Methods and Results

Surfactants

Eight substances (Table 1) were screened using the three bioassays described below. All compounds except for substance "E" were either strong surfactants, commercial detergents or both. As such, these relatively simple organic compounds are extremely stable, readily available and very inexpensive. All materials tested originate from Israel except substances A, F, and H, which were obtained from the United States, Substance E was the crude secretion of the moses sole (*P. marmoratus*)(*PMC*) This material was prepared by expressing the milky fluid from the toxin-bearing ampullae of the living fish. The secretion was immediately collected, freeze-dried and stored in a dark, dry place at 20°C. It was reconstituted to various concentrations with distilled water just prior to use. The same applies to all surfactants; these were diluted to final concentration on the day of the test.

Animals

The 41 sharks used in this study were young lemon sharks (*Negaprion brevirostris*) of both sexes. all less than 3 years old. The sharks had been maintained in the laboratory for at least 10 weeks prior to the study and all were in good health. Details of laboratory maintenance can be found in Gruber.[8]

The teleosts used in the lethality trials were pupfish (*Fundulus heterocleitus*) collected by seine net on a shallow muddy shore of Biscayne Bay near Miami. These specimens, 4 to 6 cm total length were held in the laboratory several days prior to the study.

Bioassays

Three test methods were developed to evaluate the eight substances under consideration. In all cases, substance "E" (PMC) was used as a reference. The first was a standard toxicity test in which lethal concentrations were determined. Test fish were immersed in seawater to which substances in various concentrations and combinations were added. For the second test, lemon sharks were deprived of food for 48 hours and then offered a bait with a syringe attached to it. Thus, we were able to introduce substances into the shark's mouth as it attacked the fish. For the third and final test, sharks were held in an inverted position until they fell into a transient state of inactivity known as "tonic immobility." In this state, reflex movements of the mouth during

Table 1
Test substances employed in the present study

Code	Commercial Name	Generic Name	Source
A	SDS	Sodium-dodecyl-sulfate	Sigma Company, USA
B	Tween 20	Ethoxylated (20)-sorbitan-monolaurate	N. Garti, Cazali Inst., Jerusalem
C	Brij 35	Ethoxylated (23)-lauryl-alcohol	N. Garti, Cazali Inst., Jerusalem
D	10.G.1.0	Deca-glycerol-monooleate	N. Garti, Cazali INst., Jerusalem
E	PMC	Lyophilized crude secretion of *P. marmoratus*	E. Zlotkin, Hebrew Univ., Jerusalem
F	Saponin	Mixture of Steroidic glycosides	Sigma Company, USA
G	Myrj 59	Ethoxylated (100)-stearate	N. Garti, Cazali Inst., Jerusalem
H	Triton X 100	Iso-octyl-phenoxy-polyethoxy-ethanol	Packard Co., USA

Drawing rendered from a photograph, the courtesy of Gary [illegible]

Examining the eye of a hammerhead shark

respiration permit substances to be introduced via syringe into the shark's buccal cavity, at will.

Lethality test, preliminary experiment: Pup fish were individually placed in plastic containers filled with 150 ml of sterile, filtered seawater. Prior tests established that control fish could survive 48 hours or more in these containers. Each experimental fish was acclimated for 30 mintues in the container before a test substance was added. The trials were systematically organized so that substance, concentration and exposure time were independent variables while physiological death was the dependent variable.[9] Test periods of 6 and 24 hours were used. Each of the eight test substances was individually added to final concentrations varying in log steps from $1\,\mu g{\cdot}ml^{-1}$ to $1000\,\mu g{\cdot}ml^{-1}$ (i.e., 1 ppm, 10 ppm, 100 ppm, and 1000 ppm). Thus, there were 64 possible test combinations and since two fish per trial were used a total of 128 subjects were studied. The objective of this assay was to determine:

(a) whether surfactants were lethal to (pup) fish;

(b) which of the eight substances was most toxic, and

(c) the lethal concentration of each.

Results of the preliminary experiment are shown in Table 2. We concluded from these results that certain detergents are lethally toxic to fishes and that sodium dodecyl-sulfate (substance A) and iso octyl-phenoxy-polyethoxy ethanol (substance H), both quite common, stable surfactants, are actually more lethal than PMC.

Lethality test, critical experiment: Using results from the preliminary experiment, we again tested substances A, E and H to determine the approximate LD_{50} value, (i.e., that dose lethal to 50 percent of the subjects). The sampling and calculation of the LD_{50} were performed according to the method of Reed and Muench.[9] The different doses were applied to groups of five pupfish placed together in a single container (150) ml, volume). Generally the effect on the subjects was greater than we would have predicted from the preliminary experiment. This increased susceptibility perhaps arose either from crowding during the test or the withholding of food during the several days prior to the study. The critical trials lasted six hours during which subjects were exposed to a much narrower range of concentrations than in the preliminary trials. The LD_{50} values are as follows:

1. Substance A $\sim 1.5\,\mu g{\cdot}ml^{-1}$ or 1.5 ppm
2. Substance H $\sim 6\,\mu g{\cdot}ml^{-1}$ or 6 ppm
3. Substance E $\sim 8\,\mu g{\cdot}ml^{-1}$ or 8 ppm

While these LD_{50}'s are but a first approximation, we are satisfied with the conclusion

Table 2
Lethal concentration of substances as tested on 4-6 cm pupfish, F. heterocleitus

Substance (See Table 1)	6 hour Test Period Concentration (μ g·ml $-^{1}$)			24 hour Test Period Concentration (μ g·ml $-^{1}$)					Order of Lethality
	1000	100	10	1	1000	100	10	1	
A	2 (10 min)*	2 (15 min)	1 (250 min)	0	2	2	2	0	1
B	1 (145 min)	0	0	0	2	0	0	1	6
C	2 (40 min)	2 (100 min	0	0	2	2	0	0	4
D	0	0	0	0	0	0	0	0	0
E	2 (13 min)	2 (35 min)	0	0	2	2	0	0	3
F	2 (30 min)	0	0	0	2	2	0	0	5
G	0	0	0	0	0	0	0	0	0
H	2 (15 min)	2 (40 min)	0	0	2	2	1	0	2

* *Number indicates how many of the two fish used in each trial died during the test exposure. Number in parentheses indicates time to apparent death.*

that substance A is more potent than substance E and that substance H is about equipotent. Under these test conditions, substances B, C and F are weakly toxic while substances D and G can be considered non-lethal.

These findings encouraged us to move ahead to the shark bioassays. Most interesting was the finding of a range of activities varying from completely benign to extremely lethal, within a group of related compounds. This suggested the possibility of systematically screening a number of related substances for the most effective and then improving that compound further by laboratory manipulation.

Shark bioassays

Animals: A total of 23 female and 18 male lemon sharks (61.5-84.0 cm total length and 1.3-3.0 kg wet weight) were used in the trials. Sixteen (mostly smaller) sharks were used in the feeding assay while 25 were used in the tonic immobility trials.

Feeding Experiment: Sharks were housed and tested in a 12 kl open seawater aquarium (6 x 2 x 0.5 m). The flow rate was about 80 l·min^{-1}; filtered seawater entered one end and drained from the far end of the tank. Sharks were free to swim in any part of the aquarium.

Prior to the trial, all food was withheld for 48 hours. We had previously shown that this deprivation period is adequate to motivate healthy sharks to actively feed provided that the temperature is above 25 °C (it was).[10]

After the deprivation period a whole blue runner (*Caranx fuscus*) was prepared as a bait by attaching a 25 cc syringe to it (Figure 1). The nozzle of the syringe was fitted with a plastic tube which protruded slightly out the bait's mouth.

Thus prepared, the bait was offered to the entire

Figure 1. *Feeding bioassay: a 20 cm long blue runner, **Caranx crysos**, is prepared as a bait by attaching a 25 ml syringe to the fish. The plastic tube extends out the bait's mouth.*

group of sharks. They immediately attacked it. The experimentor could then manipulate the fish with one hand so that a feeding shark grasped the bait in its jaws (Figure 2). At that point the experimentor released 15 to 20 ml of test substance into the attacking shark's buccal cavity. The results of such trials took one of three forms: (1) no effect on the shark's behavior and the bait fish's head was torn off and consumed; (2) moderate effect on the shark which either continued to feed, or more frequently, lost interest in the bait; or (3) strong effect on the shark which was obviously distressed and repelled. Activities of repelled sharks included rapidly leaving the feeding area, adjusting gills, or showing obvious signs of stress such as changes in coloration. While qualitative data were colected, the basic score was whether the attacking shark fed or not.

Results: The eight substances were tested in 41 feeding trials spread over 3 weeks. Results are given in Table 3. All substances except A and E were tested at concentrations of 50 $mg \cdot ml^{-1}$. Substances B, C, D and G did not appear to deter hungry sharks from feeding. Substances F and H were moderately effective at repelling sharks, but did not cause obvious distress. Substances A and E strongly repelled sharks. Substance E evoked a strong response at 10 $mg \cdot ml^{-1}$ and a moderate one at 2 $mg \cdot ml^{-1}$. Substance A clearly and strongly repelled sharks. Even at 0.8 $mg \cdot ml^{-1}$ *five of seven sharks tested with* substance A were repelled and showed obvious signs of distress as they sped away from the bait.

We conclude, from these tests, that sodium-dodecyl-sulfate (Substance A) is more effective at repelling captive lemon sharks than the reconstituted, lyophilized crude secretion of *P. marmoratus*. However, Substance H while not adequately tested, did not seem as promising in this feeding assay as in the fish lethality test. Saponin, a mixture of steroidic glycosides clearly repelled sharks at 50 $mg \cdot ml^{-1}$.

Tonic immobility (TI): Animals: Six male and 17 female lemon sharks from 59-84 cm total length were housed in a 6 kl closed seawater aquarium. These 23 animals were tested over a period of 11 days. Three other sharks were rejected because they were evidently quite sensitive and would not remain in tonic immobility.

The response: Also known as catalepsy, death feigning or animal hypnosis, tonic immobility is a well studied and widely occurring phenomenon in the animal world. While it has never been reported for sharks, it is known from fishes and invertebrates. Tonic immobility can be induced by a number of techniques; but most commonly by holding the subject in an inverted position. Eventually it falls into a trance-like state which can vary from a rigid posture to a relaxed condition. In lemon (and other) sharks, TI can be induced by turning the subject over so that its ventral side is up; and maintaining that position until it relaxes perceptibly (Figure 3). This requires 15-20 seconds, and the animal will remain immobilized for over 10 minutes.

In preliminary unpublished studies, Gruber and

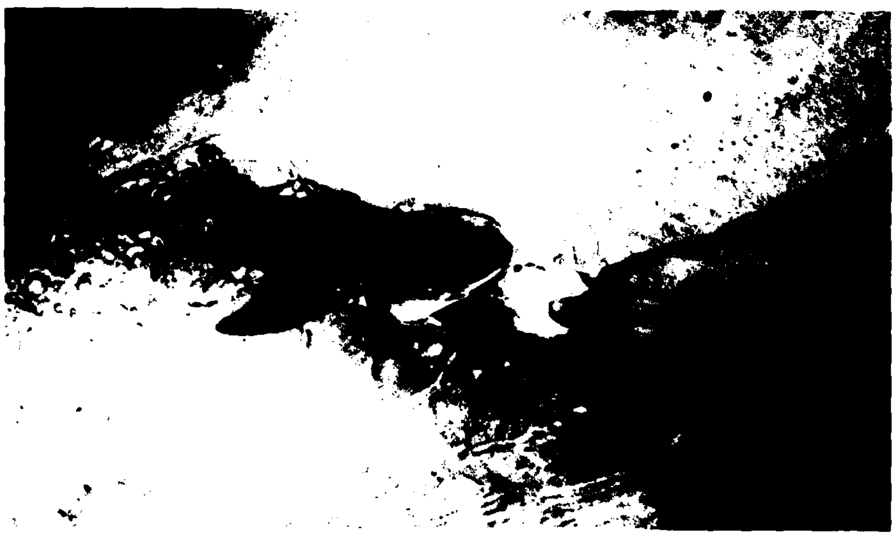

Figure 2. Feeding bioassay: an 80 cm long lemon shark, ***Negaprion brevirostris,*** *attacks the bait and grasps the head in its mouth. Simultaneously, the experimenter releases the test substance into the shark's mouth.*

Table 3
Summary of Feeding Trials

Substance	# of Trials	Concentration ($mg{\cdot}ml^{-1}$)	Result	Comment
A	13	0.8 to 100	12 strongly positive*; 1 negative	
B	6	6.4 to 50	5 negative; 1 weakly positive†	
C	2	50	1 negative; 1 weakly positive	
D	4	50	3 negative; 1 positive	
E	7	2 to 10	7 positive‡	Strong at 10 $mg.ml^{-1}$; fair at 2 $mg.ml^{-1}$
F	4	50	4 weakly positive	Insufficient testing
G	3	20	1 negative; 2 weakly positive	Insufficient testing
H	2	50	2 positive	Insufficient testing

** Strongly positive signifies that shark showed obvious signs of distress after exposure*
† Weakly positive means that shark rejected bait and swam slowly away
‡ Positive implies that shark left the bait and dashed away

Mitchell Watsky determined that lemon sharks do not habituate to TI if given less than 4 exposures per day. In this case, habituation refers to the voluntary termination of a TI by the shark in ever decreasing time as exposure to TI trials increases. This TI behavior, though seemingly unrelated to repellency, was chosen because it has an unambiguous endpoint; and because our preliminary studies had shown that TI in the lemon shark is quite resistant to termination. For example, it is possible to perform minor surgery under TI. Thus, we felt that TI might represent a rapid test behavior for screening materials for their activating qualities. Clearly the relationship and validity of TI to repellency would have to be demonstrated.

The tests: The first 61 trials established the general test procedure and crudely established the concentrations needed to terminate TI. The procedures consisted of inverting a shark and holding it on a trough which was placed inside a resin-coated plywood container of 20 l. Water entered the front of the container at 25 $l{\cdot}min^{-1}$ and simply overflowed onto the ground. The tonically immobilized shark was allowed to adapt for 3 minutes and then tested by injecting 4 ml of a substance into its buccal cavity (Figure 4). Sharks were usually given a single dose of 1, 10, 50 or 100 $mg{\cdot}ml^{-1}$ and responses were scored as positive only if the shark righted itself (Figure 5). Other qualitative responses were recorded but did not enter the scoring. In the final test, an ascending method of limits was used to approximate threshold concentrations of 4-ml doses. Here, the dose was increased from 0.1 to 50.0 $mg{\cdot}ml^{-}$ by doubling the concentration in subsequent tests (i.e., 0.1, 0.2, 0.4, 0.8 . . . 50 $mg{\cdot}ml^{-}$). The threshold concentration was arbitrarily chosen as that which terminated TI in 50% of the sharks tested (i.e., ED_{50}). For example, substance E was tested on seven sharks under TI. Each shark was given six trials with 4 ml injections in which the concentration of E was successively doubled from 0.1 to 3.2 $mg{\cdot}ml^{-1}$. A test run was terminated if the shark "awoke" on 2 trials in a row. For half the sharks tested with substance E, 0.8 $mg{\cdot}ml^{-1}$ was the effective dose needed to terminate TI and thus was considered the threshold for that substance. Table 4 shows the result of the TI studies. Again, sodium-dodecyl-sulfate (Substance A) was the most effective. It was 4 times more potent than PMC and 30-100 times more potent than its nearest competitors. Substance B gave results which were inconsistent with the other assay results. This material was quite effective at terminating TI but had no apparent effect on the feeding response.

Table 5 summarizes all three assays. The 8 test substances have been ranked according to their efficacy. There is a clear correlation between all three

tests with respect to the most effective substances (A, H and E).

Figure 3. (left) *An 85 cm lemon shark inverted and under tonic immobility. A shark will remain essentially immobile for at least 10 minutes except for breathing movements of the mouth and gills.*

Figure 4. (top) *Tonic immobility bioassay: experimenter releases a test substance into the immobilized shark's mouth.*

Figure 5. (below) *Tonic immobility bioassay: a shark "awakens" from tonic immobility after a test substance has been released into its mouth.*

Table 4
Tonic Immobility Bioassay: Lemon sharks

	Preliminary Test		Final Test	
Substance	**# of Trials**	**Threshold (mg·ml − ¹)**	**# of Trials**	**Threshold (mg·ml − ¹)**
A	14	1	33	0.2
E	16	10	29	0.8
B	9	1	45	6.4
H	16	50	26	25
C	10	50	2)†	-
G	7	50	-	-
F	7	100	-	-
D	6	1)*	-	-

** No effect at 100 mg.ml-¹*
† No effect at 50 mg.ml-¹

Table 5
Comparative Results: Test substances ranked in order of potency

Lethality (Pupfish)	Feeding (Lemon shark)	TI (Lemon shark)
A	A	A
H	E	E
E	H	B
C	F	H
F	B*	C
B	C*	G
D*	D*	F
G*	G*	D*

** No apparent effect at test concentrations.*

DISCUSSION

This work was undertaken to serve two purposes: (1) develop a rapid bioassay using sharks as subjects in repellency trials and (2) to use the developed assays to test the theory that detergent-like properties of paradaxin underly its shark-repellent qualities. With regards to the first purpose, the two test procedures using captured lemon sharks kept under controlled conditions proved simple to perform and relatively unambiguous in their result. Thus interpretation of the behavioral endpoints was kept to a minimum and quantitative results were possible. Of course there are some practical drawbacks to the use of unconditioned responses. These include habituation and lack of motivational control. Thus, a third assay, employing (operantly) conditioned sharks should be developed. Nevertheless, the good correlation between the results of all three bioassays suggests that tonic immobility can be employed as a sensitive and reproducible test to rapidly screen large numbers of substances. Concerning the second purpose of this report: given the background of the present data, it is premature to ascribe the repellent properties of these substances to their amphipathic and surfactant properties. This is because only four of the seven surfactants were actually repellent. Nevertheless, results of this study have confirmed our prediction that detergents repell sharks; and that one fact opens up a host of possibilities for further studies at both the theoretical and practical level.

Of the seven surfactants we studied, SDS was by far the most effective shark repellent. SDS is a well known, potent detergent and foaming agent which can be immediately distinguished from the other surfactants we tested by the presence of a sulfate functional group and its ionic and strongly hydrophylic nature. These very characteristics may serve as guidelines for future experimentation.

Finally, it must be emphasized that these are preliminary results. The reader should not infer from this study that SDS or any other detergent will protect a swimmer from shark attack. It is for this reason that we intend to pursue this line of research with the eventual goal of providing a highly effective chemical shark repellent. The task ahead will require behavioral testing and laboratory modification of many compounds along with physiological and anatomical study of the effects on the shark of repellent compounds. ■

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*Dr. Eliahu Zlotkin is Assistant Professor of Zoology at the Hebrew University, Jerusalem, Israel. He is known for his research in the area of insect toxicology. He has been studying, under Office of Naval Research contract, shark repellants; most recently, the effects of the toxin of the moses sole (**P. marmoratus**).*

The Coastal Environmental Reference Service

by

Suzette K. May, Robert Dolan,
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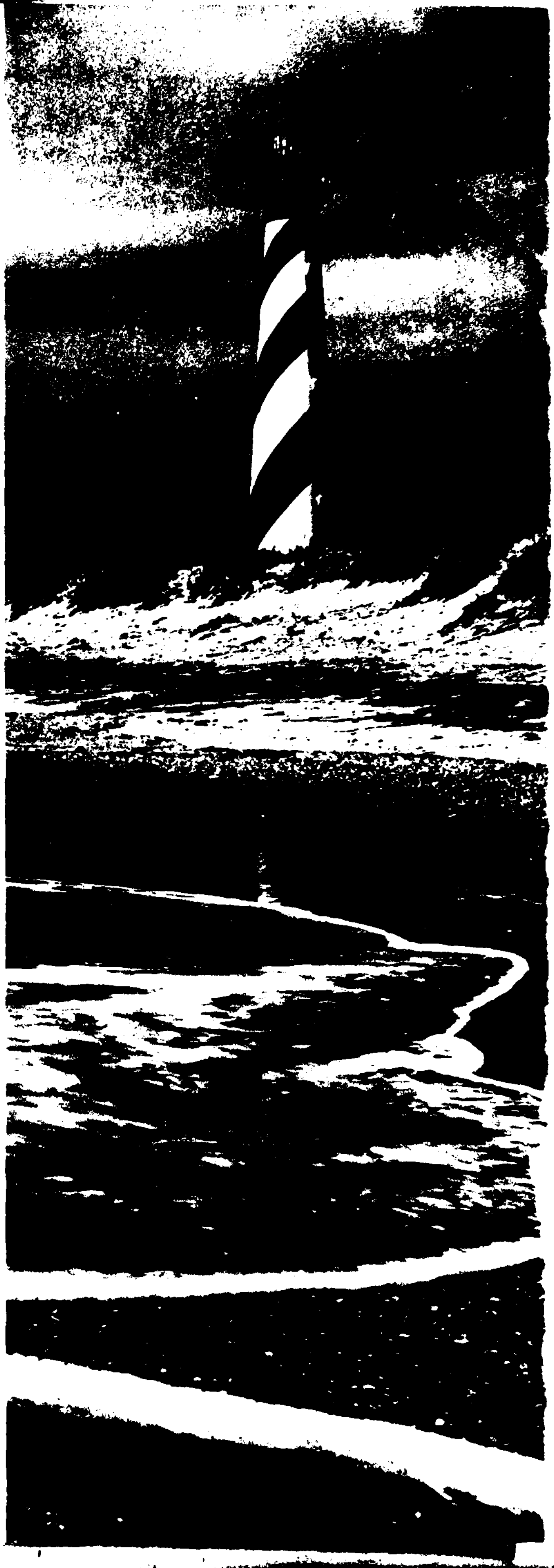
University of Virginia,
Charlottesville



The lighthouse at Cape Hatteras, North Carolina, in 1953. This historic landmark is in danger of being destroyed because of rapid shoreline erosion. However, this process is not unique to this site. Rapid shoreline change is occurring on most of the world's sedimentary coasts. (Photo by Ralph Anderson, National Park Service).

Introduction

In 1977, we reported in *Naval Research Reviews* on the design of a coastal information management system developed at the University of Virginia under a research contract from the Office of Naval Research.[1] At that time, the system was operational as part of the SHARP computer base at the Naval Ship Research and Development Center (NSRDC) in Carderock, Maryland. During the past four years, the system has undergone significant modifications, including a change of location, and a third query mode has been added. In this paper we will outline those changes and describe the new analog query mode. Examples of actual analog runs will be used to illustrate the increased usefulness of the system.

UVAIS Development

The University of Virginia Information System (UVAIS) was originally developed to satisfy a perceived need of the Navy's data management network. As a Navy contractor, we were aware of the commitment that the Navy has to data acquisition. Much of the data that are collected by or for the Navy may not fully be used to benefit naval operations because of storage, retrieval, and delivery problems. In many cases there is a five-year delay between the time data are collected and when they are interpreted and available for the Fleet.[1] Additionally, the Navy has no provision for the centralized control and storage of such data. Different data are necessary for individual projects, so each user will construct a localized, specific data bank.

UVAIS was developed as a unified, standardized means for cataloguing the existence of coastal data. There are several benefits to this approach. Gaps in data coverage can be identified immediately. Additionally, a centralized system encourages the standardization of data collecting and reporting and increases the frequency of data exchange among researchers. This is important in overcoming reluctance to use unfamiliar data sets and also makes comparisons among different data sets more feasible.

It is unrealistic to attempt to bring all data into one system. The large, multi-purpose data access systems, such as Environmental Data Index/Oceanographic Atmospheric Scientific Information System, illustrate some of the problems associated with an all-encompassing system. It is difficult to design a finely tuned query and a large volume of extraneous information is often delivered. Therefore, UVAIS was designed as a special purpose system providing maximum accessibility to those data sets with relevance to a specific topic: the coastal zone.

The study of coastal areas is of particular interest to the Navy because an understanding of process behavior in these areas is essential to amphibious, coastal patrol, and Navy Underwater Diving Team (Seal Group) operations. Operational planners need accurate, timely information on conditions of shorezone and nearshore areas and must

Patterns of overwash deposits on the Chandeleur Islands, Louisiana. Such patterns are typical of the 295 barrier islands that rim the Atlantic and Gulf coasts. Recent research suggests that these deposits are periodic through both space and time.

have a means of locating and transferring relevant data sets. Computerization of the coastal information system is necessary for efficient storage, retrieval, and update of the large volume of material involved. UVAIS was originally implemented as part of the Ship Analysis and Retrieval Program (SHARP) which is a generalized data-base management system housed at NSRDC. All original design and testing took place under the aegis of that system.

CERS:
Coastal Environmental Reference Service

In 1980, it was apparent that the information system had outgrown the available working space in the SHARP system. Over 5,000 records were available to system users and the coverage of new operational areas was being planned (Table 1). The analog query mode had been designed and was ready for implementation. In order to accommodate the increased size of the system and make it more accessable to operational Navy users, the Navy made a decision to transfer the entire system to a new facility.

The Naval Oceanographic Office (NAVOCEANO) in Bay St. Louis, Mississippi, has long been a primary generator, collector, and user of oceanographic data. The UNIVAC computer facilities at Bay St. Louis are much larger than those available for our contractor research and development use in Carderock and could easily assimilate the coastal information system. NAVOCEANO has developed an Oceanographic Management Information System (OMIS) which is housed at Bay St. Louis. The OMIS is an automated system developed expressly to monitor collectively and make available information on various programs, requirements, assets, technology, and data pertaining to naval oceanography, meteorology, and mapping, charting, and geodesy.[2] The coastal information system, renamed the Coastal Environmental Reference Service (CERS) has been assimilated into the parent OMIS structure.

A tutorial mode of query, similar to that used with the SHARP system, was programmed specifically to meet the needs of the researchers that would be accessing CERS. Through the use of remote terminals, a user may access the system and design a query suited to his particular needs, facilitated by a computer prompt/response program (Figure 1). Information sections are available at each stage of the query for users unfamiliar with the program, as are "HELP" sections of explanation (Figures 2a and 2b). The output format has been streamlined to assist the researcher in his analysis (Figure 3). If a user is familiar with the CERS, an advanced query mode will save time and reduce the cost of accessing the system (Figure 4).

The CERS concept is effective because of the

TABLE 1
*Inventory of CERS Type 2 Records**

	GMX	NAT	SAT	NPC	SPC	MED	CAR	NTH	ARC	GCA	BLT	PSG	TOTAL
Waves	58	335	1	144		1	4	131	8	1	1	1	685
Tides	59	143	3	107	4		2	68	2	1	1		390
Currents	20	49	3	118			3	45	2		8	1	249
Winds	187	360	3	504		12	2	115	30		11		1224
Bathymetry	42	138	2	12			2	16	1		1	1	215
Sediments	37	166	2	95			2	50		1	1	1	355
Beach Morph.	44	286	2	109			1	16	3		1	1	463
T.D.S.†	26	81	1	94			3	37	5		24		271
Meteorological Parameters	185	369	1	463		12	2	83	32		10		1157
TOTAL	658	1927	18	1646	4	25	21	561	83	3	58	5	5009

† temperature, density, and salinity
* Current through 3/81
GMX = Gulf of Mexico; NAT = North Atlantic; SAT = South Atlantic; NPC = North Pacific; SPC = South Pacific; MED = Mediterranean; CAR = Caribbean Sea; NTH = North Sea; ARC = Arctic Ocean; GCA = Gulf of California; BLT = Baltic; PSG = Persian Gulf.

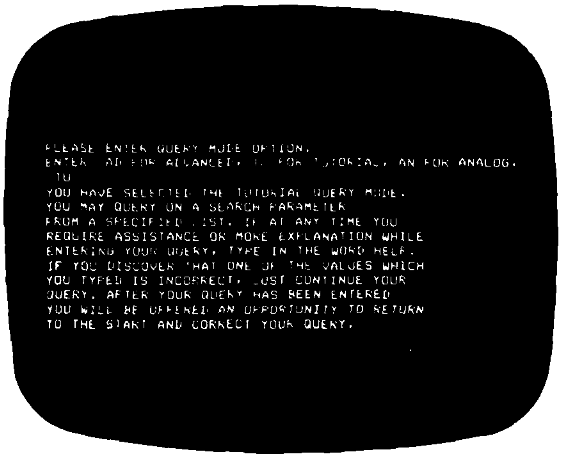


Figure 1. CERS tutorial introductory explanation.

continuing relationship between the data contributors and the data users. Updating records and adding new records is a continual process. If CERS suits the particular needs of a coastal data manager in making information about his data available in an automated fashion, he is encouraged to participate in the expansion of the data base as a regular contributor. Coastal scientists wishing to become part of the system should contact Dr. Robert Dolan, Department of Environmental Sciences, 101 Clark Hall, University of Virginia, Charlottesville, Virginia, 22903 ((804) 924-3809). Navy units with particular operational needs are encouraged to contact Mr. Richard Blumenthal, NSTL Station, Naval Oceanographic Office, Code 5003, Bay St. Louis, Mississippi, 39576 ((601) 688-4497).

The Analog Component

Naval operations planning often requires information about areas that have not been extensively studied or whose data sets are inaccessible because of political or logistical considerations. Nevertheless, information about coastal processes is necessary. In such cases, an information system query will locate neither sufficient data inventory files nor an appropriate geophysical model. Records for adjacent areas may be retrieved by enlarging the area of search (latitude/longitude parameters); however, this risks receiving extraneous and/or erroneous information. A difference of 10° latitude, between North Carolina (35°N) and the Florida Keys (25°N), for example,

Figure 2a. Sample tutorial query

Figures 2b. Sample tutorial query.

results in information for coastlines that are very dissimilar.

The analog, or data transfer, mode seeks to alleviate this problem. This mode of query is predicated on the hypothesis that coastal processes will act in a similar fashion along coasts that are physically similar. In other words, one might expect a storm of a given duration and intensity to cause the same types of damage or changes along two separate reaches of coast that share similar physical attributes such as beach slope, orientation, bathymetric profile, sediment size, and geology. This concept is currently being tested quantitatively.

The CERS system design has a very specific focus: to give information about the design and availability of data sets. No "hard," or actual, data have been included. In order to make the analog mode a functional component of the system, certain hard data must be included. These data are those pieces of information which characterize a coastal site. The diagnostic parameters are used as the basis of a search and match query; however, they are not included in the record output for a site. The parameters designated "diagnostic" must satisfy two criteria: (1) they must be site-specific features, not regional trends; and (2) the information must be readily accessible in common-knowledge sources such as atlases, charts, maps, or published reports.

At present, 16 parameters are being used to characterize each site already in the system. These data have been appended to every record previously attached to the system and are routinely included in every new record as it is entered. Values for each parameter are generally available in non-classified sources for most coastal reaches worldwide. It is not necessary to enter a value for every parameter in order to make a successful analog run. However, the user should keep in mind that as more information is made available to the computer, a more reliable match can be achieved. The 16 parameters now in the system are:

1 Coastal Landform Type—Regional Geology
2 Coastal Landform Type—Relief
3 Coastal Landform Type—Shoreline Character
4 Waves—Significant Breaker Height
5 Waves—Wave Climate Class
6 Tidal Range
7 Tidal Type
8 Storm Frequency

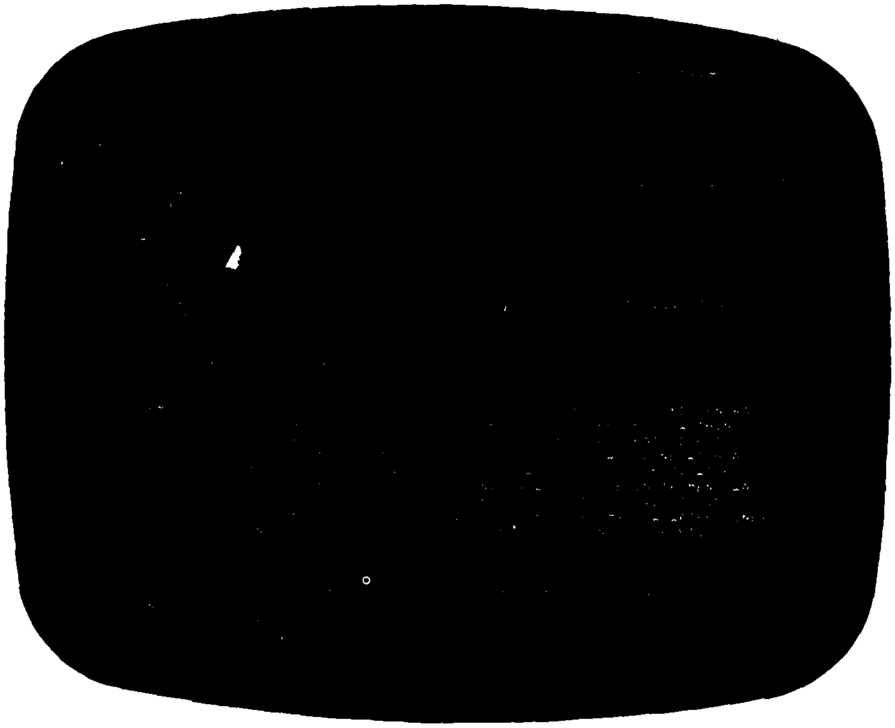


Figure 3. CERS Type I record.

9 Beach Materials—Particle Size
10 Beach Materials—Particle Type
11 Bottom Materials—Particle Size
12 Bottom Materials—Particle Type
13 Coastal Orientation
14 Offshore Configuration
15 Wind Speed
16 Wind Direction

The analog program will search the record files for those sites with matching values for the parameters entered. It will print a list of those record identification numbers that have matching features and the number of parameters that did correlate. The user is then directed to access the system in the normal modes to see specific records. Like the tutorial and advanced query modes, the analog mode delivers no hard data. The analog system will not predict processes, nor is there a guarantee that the data, once acquired from the listed source for a particular area, will be directly applicable to the user's needs. The system will, however, provide an estimate of what one might expect to find in the data-poor area. The user is provided with a list of contacts and thus learns of others doing similar work in an environment similar to his. These sources may, in turn, lead the user to pertinent information in areas closer to his own. Additionally, the user will know what type of work has or has not been effective in similar coastal environments.

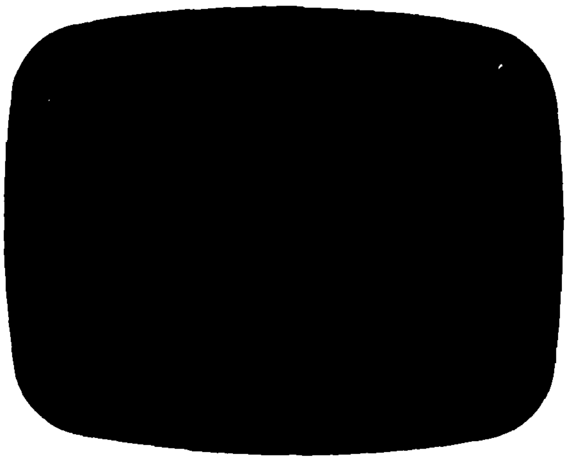


Figure 4. Sample advanced query.

Coastal studies are conducted to provide the Navy and Marine Corps with an improved capability to accurately predict the ever-changing conditions of the coastal environment.

System Access: The Analog Component

The analog component has been designed with more complexity than the other parts of the system. More input is required from the user, and more information must be available before a query is initiated. Therefore, this component is available only in the tutorial mode.

The computer begins the interaction by ascertaining if the user is already familiar with the system. If the user has not used the system before, he may wish to have an explanatory section printed (Figure 5). This section lists the parameters used to determine the analog and describes how the program makes the search. The user is cautioned that the analog search is not recommended if information is available for fewer than 8 of the 16 parameters. The reliability of the analog increases with the amount of data that the user can supply for his area of interest. If, at any time during the query, the user is unsure of how to proceed or questions the method used to calculate a value for a particular parameter, he may type "HELP" for additional explanations. To continue with a query, one must enter the indicated codes of those parameters for which information exists (Figure 5).

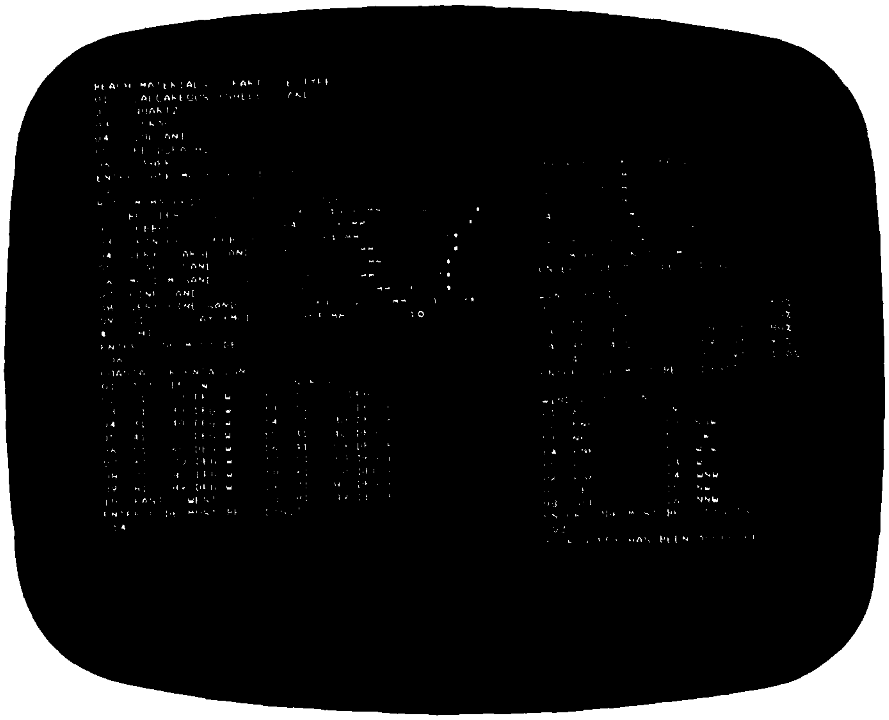
In the example here, we chose a site at random on the southeast coast of Africa (Port Durnford, Zululand). This region was selected because it is an area of political uncertainty and a constant, reliable flow of data from the region could not be anticipated. A query to the system indicated that no data collection program was in effect that could be accessed. A computer literature search showed a published article describing the area in general [1]; we were able to define 14 of the 16 parameters from this article.

Figure 5. Analog component—explanatory section.

Figures 6a and 6b illustrate the query process as these 14 variables were entered. If no mistakes are made in the entry format, the computer will inform the user that his query has been accepted. After a short wait, those records that match at least two- thirds of the input variables are listed with the number of matching parameters (Figure 7).

The list of analog record identification numbers is followed by instructions for retrieving any records that the user wishes to see. By entering the system in the advanced mode, specific records can be requested (Figure 8). In this way, the user can select the level of correlation that he is willing to accept. Figure 8 shows the records for the highest level attained in this query (11 matches out of a possible 14). These records indicate that out of the 5,000 records in the system representing locations in Europe, North America, South America, and Asia, the reach of coast most physically similar to the Zululand area is Cape Lookout, North Carolina. The Cape Lookout area has been studied extensively in terms of both physical characteristics and coastal processes, and those data sets will provide an estimate of the conditions in an area which is considerably less accessible.

Figures 6a and 6b. Sample analog query.



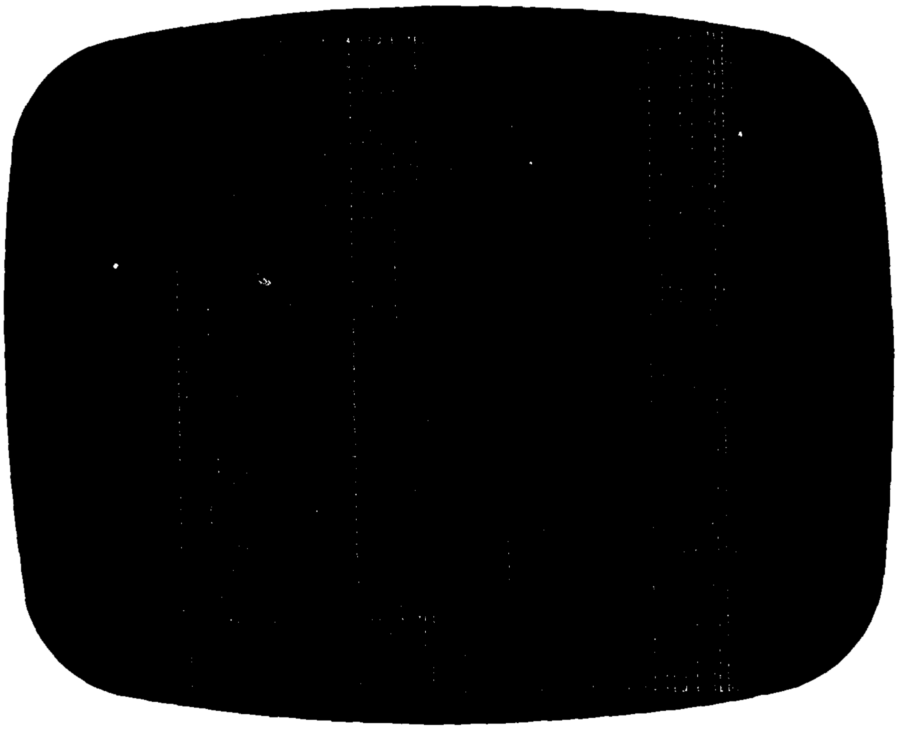


Figure 7. Analog mode output.

```
IN ORDER TO RETRIEVE THE ABOVE HITS YOU MUST ENTER
THE ADVANCED MODE OF CERS. AFTER THE STATEMENT
'PLEASE INPUT QUERY COMMANDS' YOU MUST ENTER
    IF RCDID = XXXX-XXX
    REPORT TP2
    $END
WHERE 'XXXX-XXX' = RECORD ID ON THE ABOVE PRINT OUTS.
WOULD YOU LIKE TO SUBMIT ANOTHER QUERY (Y OR N)?
>Y
PLEASE ENTER QUERY MODE OPTION.
ENTER  AD FOR ADVANCED, TU FOR TUTORIAL, AN FOR ANALOG.
 AD
PLEASE INPUT QUERY COMMANDS
 IF RCDID =0047-350
 REPORT TY
 REPORT TP2


 $END
YOUR QUERY HAS BEEN ACCEPTED.




                 INFORMATION ON DATA COLLECTION SITES

REPORT  TP2                                              AUG 10 1981

RCDID        0047-350
COUNTRY      UNITED STATES       OCEAN       NORTH ATLANTIC
LATITUDE     343600N
LONGITUDE    0763200W

CAPE LOOKOUT, N.C.
COAST GUARD STATION
POC-NAME     DIRECTOR, NATIONAL CLIMATIC CENTER
POC-INST     FEDERAL BUILDING
POC-ADD      ASHEVILLE, N.C. 28801
POC-PHONE    704-258-2850

AXSHORE      ONSHORE                         STATUS     ACTIVE

PERIOD-NUM   01         02         03         04
STARTDATE    JAN 67     SEP 72     APR 61     MAR 71
STOP-DATE    AUG 70     DEC 75     MAY 67     DEC 75
LENGTH-YR        3.66       3.33       6.17       4.81
DATA-GAPS    21 30 PCT 0-10 PCT  21 30 PCT 0-10 PCT

PERIODS      1-3        1-3        1-3        1-3        1-3        1-3

DATA-FREQ    1/HR       1/HR       1/HR       1/HR       1/HR       1/HR

RCD LENGTH
RCD FREQ
VARIABLE     SURFACE AIR TEMP.   SL BAROM. PRESSURE  SURFACE PRECIP.
             SURFACE DEW POINT   SURFACE VISIBILITY  SOLAR RADIATION
METHOD

REMARKS      ONLY 3-11 OBSERVATIONS PER DAY IN PERIODS 1 2 AND LESS THAN
             3 IN PERIOD 3. CONTINUOUS BAROGRAM RECORD AVAILABLE FOR
             PERIOD 4.
```

Figure 8. Record retrieval from the analog search mode.

Conclusion

The University of Virginia information system has been transferred to the NAVOCEANO computers in Bay St. Louis, Mississippi. At this facility, it has become part of the OMIS master program and renamed the Coastal Environmental Reference Service (CERS). The change in computer hardware and software has permitted the reprogramming of the system so that it is easier to access. Explanations have been rewritten in response to user suggestions so that the tutorial mode of query is clear even to users with no prior computer experience. The OMIS parent program is structured such that a query can be processed quickly with little extraneous information delivered.

With the change in location, an analog mode of query has been added. The analog component permits a user to access information about data in areas that are physically similar to a data-poor area. This mode has potential for operational Navy planning in areas that are inaccessible to direct sampling.

CERS is operational at all three access levels. In the future, the analog component will be expanded to include statements about the statistical significance of the analog correlations and analyses of the persistence of the characteristic variables chosen by the user. Currently, over 5,000 records are in the files, representing sites on all continents. Update of existing records and addition of new records for areas of Navy interest are continuing processes. The usefulness of such a system is dependent upon the information contributed by coastal scientists and the definition of focal areas as determined by specific naval units. Anyone interested in contributing to or accessing the system is encouraged to contact the authors. ■

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ONR sponsorship of geographical research has found refraction to be a major dynamic coastal process occurring in varying degrees along all coasts of the world. Note how the wave direction and energy are refracted almost 180° around the small atoll.

Dr. Robert Dolan is Professor of Environmental Sciences at the University of Virginia. In his research career he has focused on regular along-the-coast variations in coatal landforms. The data sets used in his publications are the result of a program to acquire meso to regional scale shoreline change data. He received his doctorate in coastal processes at Louisiana State University. In the mid-1970's he served as Liaison Scientist for the Office of Naval Research, London.

Dr. Hayden is Associate Professor of Environmental Sciences at the University of Virginia. He received his undergraduate education at Pennsylvania State University and his PhD from the University of Chicago. Since joining the faculty at the University of Virginia, he has worked closely with Dr. Dolan on designing experiments and on the analysis of coastal data sets to describe regional-scale shore-zone processes. His publications include contributions in coastal meteorology, ecology, geology and management.

Suzette May holds degrees from the College of William and Mary and Ball State University. For the past two years, Ms. May has worked with the Coastal Environments Group at the University of Virginia where she has been involved with the design and implementation of computerized information systems. Her research has concentrated on the definition, classification, and prediction of analog coastal environments and the numerical analysis of coastal processes. Ms. May is currently completing her PhD in Coastal Processes at the University of Virginia.

The Marine Corps has increasingly emphasized preventive maintenance of the entire range of equipment from rifles and 782 gear to trucks, tanks, and aircraft. However, short of detailed inspections of each piece of equipment, there has not been a positive way to ensure that preventive maintenance was, in fact, being performed.

The Office of Naval Research contracted with Dr. Judith Komaki, of the Engineering Experiment Station of Georgia Tech, to explore the problem of organizational maintenance. Dr. Komaki is an expert in a relatively new field, the behavioral analysis of work performance. Although her research is still in progress, the following article describes the results of the first year-and-a-quarter's endeavors.

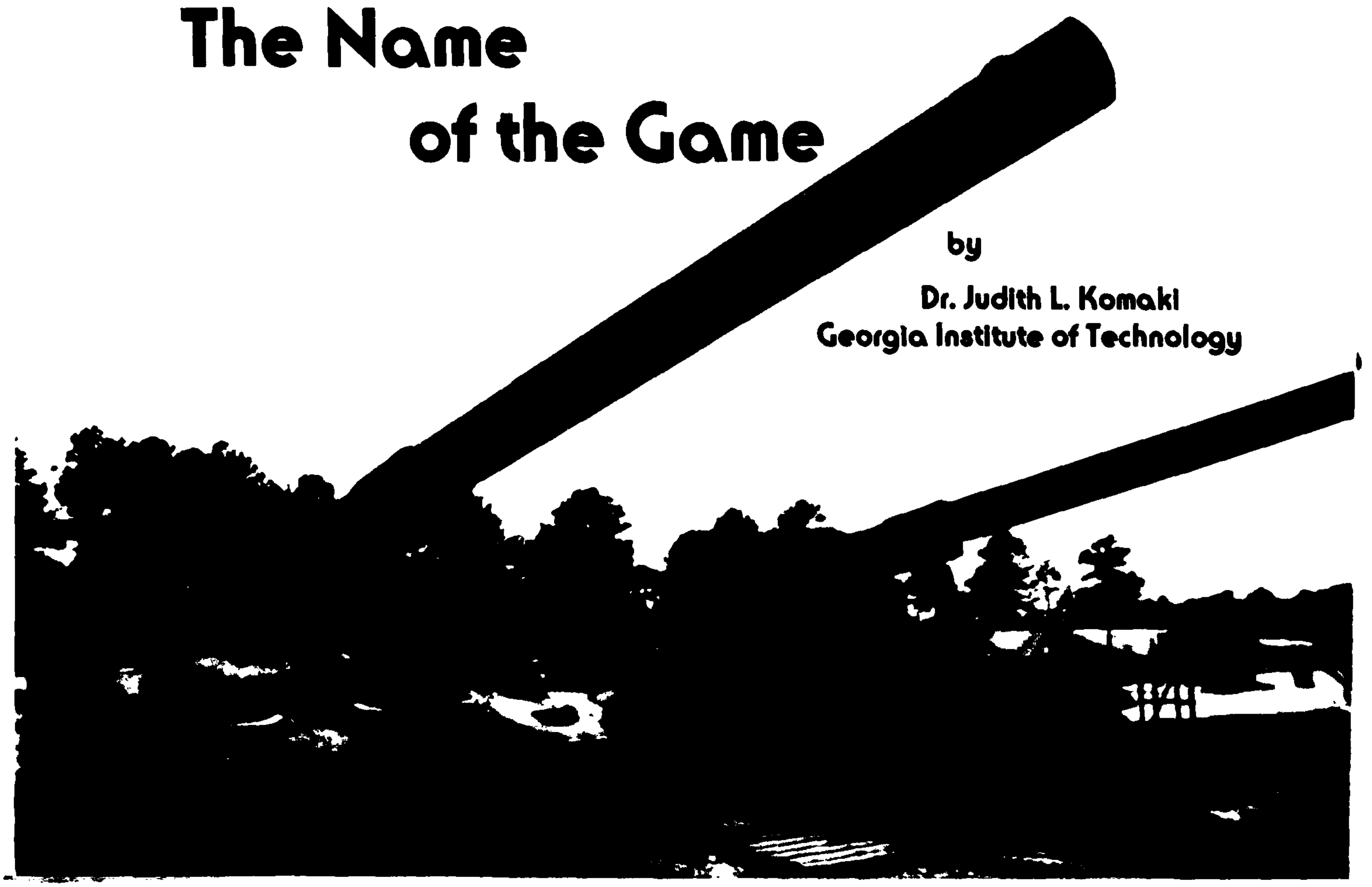
A self-propelled artillery Battery of the 2nd Marine Division was the test unit, and the study concentrated on motor transport and tracked vehicles, two complex and maintenance-heavy commodities. Dr. Komaki explored exactly what preventive maintenance entailed, who had to do it, their competency, motivation, and availability, as well as the many training and administrative requirements that detract from the maintenance mission. Her work in this "real world" of an ongoing unit highlights some surprisingly strong areas and some predictably weak areas of the current maintenance programs. Her suggestions about how to improve maintenance can potentially produce a better-higher-quality maintenance program. These proposals make the individual Marine more aware of what he has to do, and give the section head, platoon leader, and, ultimately the commander, effective tools to monitor and sustain their preventive maintenance (PM) programs.

Maintenance Management Officer,
2nd Marine Division

Preventive Maintenance: The Name of the Game

by

Dr. Judith L. Komaki
Georgia Institute of Technology



Would you be willing to coach a team in a game which you would always know if you had lost never known if you had won? A game in which your players could be pulled off the field at any moment? A game in which you always had the lowest priority choices in the player draft? I bet you wouldn't.

Yet, the coaching job I just described is the position of every section head, platoon leader, and commander in the Marine Corps today with regard to preventive maintenance.

They can't tell whether they've won because they can't even tell whether maintenance was performed or not on any given day. Howitzers in the gun park and vehicles in the motor pool look virtually the same after a maintenance check as they do before. Certainly, completed paperwork does not necessarily reflect the maintenance effort. Deadline rates (percentage of combat-essential equipment that is inoperable) are, at best, only indirect measures because they reflect many factors of which PM performance is only one.

Unfortunately, the only time most Marines hear about preventive maintenance is when they've already lost the game. A major mishap occurs (e.g., one quarter of a unit's trucks are deadlined because of transmission problems) and the repercussions reverberate up and down the line.

But I'm getting ahead of the game. Let's start at the beginning: In the fall of 1978, I was contracted by the Office of Naval Research to look into the personnel aspect of maintenance. Besides the perennial problems with the supply system and the design and use of equipment, there were problems in getting Marines to do the job, particularly at the first and second echelon levels where maintenance is not a full time duty. The goal of the research was to design a system for ongoing units to ensure that maintenance is done properly and regularly. A site, a heavy artillery Battery in the 2nd Marine Division, was selected. What I initially did, with the assistance of my colleague, Dr. Robert Collins, was to analyze the current PM system to see whether it contained the components essential to effective performance.

How the Maintenance System Works

Do Marines Know What To Do?

The first issue we set out to clarify was the technical expertise of maintenance personnel. We needed to answer two central questions:

- Are desired practices clear?
- Is training adequate?

To determine if maintenance personnel clearly understood what they had to do and had been adequately trained to do it, we devised two types of questions to assess their knowledge.

1. *Identification.* Example: "Can you identify the fill plug on the steering gear box?"

2. *Activity.* Example: "What do you do when checking the oil level in the engine compartment? What do you look for?"

Three individuals from Motor Transport and three from Ordnance were selected randomly each week. Each was asked three Identification and three Activity questions. We calculated the percentage of questions answered correctly for each section.

The questions were limited to top-ranking items on the Weekly PM Checklists. On-site personnel rated the importance of all items using a seven-point scale, and the results were used to establish listings. In the Motor Transport section, for instance, select items were rank ordered as follows:

1. Brake fluid
20. Starter/accelerator
40. Air cleaner/breather cap
60. Seats

The questions devised included the top-ranking 25 items on the lists. We used the information obtained from the knowledge appraisal to find out if personnel were technically qualified to conduct the PM checks.

Training and Knowledge of Marines Okay

Despite the general opinion that training is poor and the expertise of personnel inadequate, we determined that the knowledge level of personnel was *not* responsible for poor PM practices. The Marines in Motor Transport answered their questions correctly 99% of the time, while those in Ordnance scored correctly 94% of the time. Consequently, we concluded that maintenance was not below par because of a lack of technical expertise on the part of personnel. The men clearly knew what they were expected to do and how to go about doing it.

Can We Tell How Well Marines Do Their Job?

Next, we analyzed the kind of information onsite personnel used to judge maintenance performance. In an area such as preventive maintenance, it is important that the standard for judgment be: (1) *direct*, so that it assesses personnel performance; (2) *frequent*, so that it captures what personnel are doing on an ongoing basis; and (3) *objective*, so that it reflects in a factual, unbiased way how well personnel are doing.

Consequently, we needed answers to the following three questions:

- *Do the indicators reflect performance directly?*
- Is the information collected at least monthly?
- Is the information objective?

One frequently mentioned indicator was the *deadline rate*, the percentage of combat-essential equipment that is inoperative. *We found the deadline rate to be inadequate as a measure of PM performance, primarily because it does not directly reflect performance.* Instead, it reflects vehicle condition. Preventive maintenance practices do, of course, affect vehicle condition, but so do other factors such as the age, use, and design of the vehicles; the supply system; and the availability of funds and personnel. More important, evidence of maintenance neglect often does not surface in vehicle condition for months or even years. As a result, it is not possible to assess current PM practices by relying solely on information about present vehicle condition.

A second index is the yearly evaluation of a unit's field supply and maintenance efficiency (FSMAO). During this evaluation, an analysis team spends a week on-site, talking with Battery and Battalion personnel and sifting through records. This analysis is done to determine whether the unit is complying with Marine Corps directives and publications. After the analysis, the team writes a report which outlines all deficiencies. The FSMAO report is forwarded both to higher-level personnel, who use it to evaluate the performance of unit personnel, and to unit personnel, who are expected to correct all discrepancies immediately.

The FSMAO report, although it more directly reflects the performance of a given unit, is also not sufficient as an ongoing measure of performance, primarily because it is only done annually. One problem with an annual, preannounced evaluation is that it is time-specific and may not accurately reflect how personnel perform the rest of the year. A second problem is that an annual assessment necessarily emphasizes those aspects that have tangible products, for example, submitted tool kit requisitions, established pre-expended bins, and properly prepared equipment records. Unfortunately, finding the paperwork, tools, and repair parts in proper order does not mean that maintenance was accomplished during the previous year. Personnel could complete what they like to refer to as "paper PMs" without ever touching a vehicle.

The third indicator is the Limited Technical Inspection (LTI). LTIs are done to determine the extent and level of maintenance required to restore the equipment to a specified condition. Standard forms are used. When "excessive" discrepancies are found, the discrepancies are brought to the attention of higher-level personnel who, in turn, notify unit personnel, who are expected to rectify the situation.

Unfortunately, we also found LTIs to be lacking as a measure of PM performance. Like the deadline rate, they reflect vehicle condition, which is weighted heavily by factors other than current PM practices. Many doubts were also raised about the accuracy of the information being obtained during the LTIs. Items on the standard LTI form often are so briefly and vaguely stated (e.g., engine) that it becomes difficult for even well-trained personnel to agree about whether an item should be checked satisfactory or unsatisfactory (i.e., needs repair, adjustment, or replacement).

A New Way to Measure Maintenance

Because there was no suitable index of maintenance performance, we designed a measurement system that was direct, frequent, and objective. Retired Marines went weekly to the gun park and motor pool and recorded the performance of Marines in three areas: (1) Utilization of time during scheduled maintenance periods (number of Marines working (2) supervision during the above periods (percentage of time supervisor present), and (3) extent of corrective action taken (percentage of follow-through).

Are Marines Properly Motivated?

Next, we analyzed the work environment itself. To determine how and if personnel were being properly motivated to perform well, we asked the following questions:

- Are there any consequences for performance?
- Are these consequences related to performance?
- Are organizational incentives related to performance?
- Is there a balance of consequences for desired and undesired performance?

We directed our attention to the consequences of performance, those events that occur to the individual following his or her performance. Examples of consequences include the actions of superiors, peers, and subordinates, as well as organizational incentives such as promotions and salary increases. The reason we focused on consequences is that in work setting after work setting, dramatic improvements have occurred when consequences were frequent and related to both desired and undesired performance. Motivating personnel to improve and maintain their performance is extremely difficult when it makes little difference whether they behave in a desired or undesired manner.

Motivation Lacking

Our study of the PM environment revealed that personnel were not being motivated properly. There were few favorable consequences for desired performance. Because there were no accurate measures of PM performance, as we have seen, there was little recognition of performance, good or bad, on a day-to-day basis. It was difficult to tell when, how, and if the job had been completed. As a result, it was rarely noted in formal appraisals. Even the natural, satisfying consequence of seeing the equipment running efficiently was frequently aborted. When first echelon personnel correctly identified discrepancies during weekly PM checks, follow-through action was seldom completed promptly. Minor repairs and adjustments were not made, parts were not ordered, vehicles were not sent for repair. Only when the vehicles finally broke down were these taken care of.

On the other hand, when preventive maintenance was not completed, there also were few consequences. Again, since it was difficult to determine when PM had not been done, little corrective action was taken. Uninspected vehicles not only do not look different than inspected ones, but evidence of maintenance neglect often does not surface for months or even years. Little was said or done when the vehicles continued to operate. As long as there are no consequence for neglecting maintenance, personnel will continue to relegate PM activities to a lower status.

The only time personnel heard about the area of preventive maintenance was when a major mishap occurred. A management approach in which persons receive feedback only when problems surface is generally referred to as management by exception. There are two problems associated with this approach. First, it lends itself to crisis management. When a crisis such as the one above occurs, attention is focused on preventive maintenance. However, when another crisis occurs, attention immediately shifts to the other areas and then maintenance is forgotten in the shuffle of more measurable commitments.

The second problem is a focus on exceptional events that do not necessarily reflect performance. In the case of equipment failure, it is often difficult to determine whether breakdowns are caused by equipment design or maintenance neglect. Even if maintenance were the reason, the neglect may have occurred long before the present personnel arrived.

In summary, we were forced to conclude that the PM environment, with its lack of consequences for both desired and undesired performance, was not at all conducive to efficiently motivating personnel. On the basis of all the findings detailed above, we recommended that more frequent consequences be arranged for desired performance and that performance feedback be provided.

PM Liberty Call Program

To achieve these ends, we designed a measurement system that directly, frequently, and objectively reflected maintenance performance and we used the information it produced to provide more frequent consequences for desired performance. The consequences were a limited amount of time-off each week and weekly feedback.

The PM Liberty Call Program, as the program was dubbed, ran as follows: If all PM goals were met for the week, then an early liberty call was established for the entire Battery. Specifically:

- Monitors communicated the week's results by the close of business Friday.
- The Battery Commander announced the results no later than the Monday morning assembly.
- Early liberty was scheduled for the first available (preferably the following) Friday.
- When the Program was in effect for Motor Transport, it alone could earn the entire Battery early liberty.
- When the Program was in effect for both Motor Transport and Ordnance, both would have to meet the goals to earn the entire Battery early liberty.

Feedback was also provided each week in the form of a graph posted at Battery Headquarters.

The PM goals were determined by on-site personnel in conjunction with project staff and in reference to previous performance levels. The goals set for each of the areas are shown below:

Performance Areas	Sections	
	Motor Transport	**Ordnance**
Time Utilization	3	3.5
Supervision	50%	67%
Action Taken	67%	75%

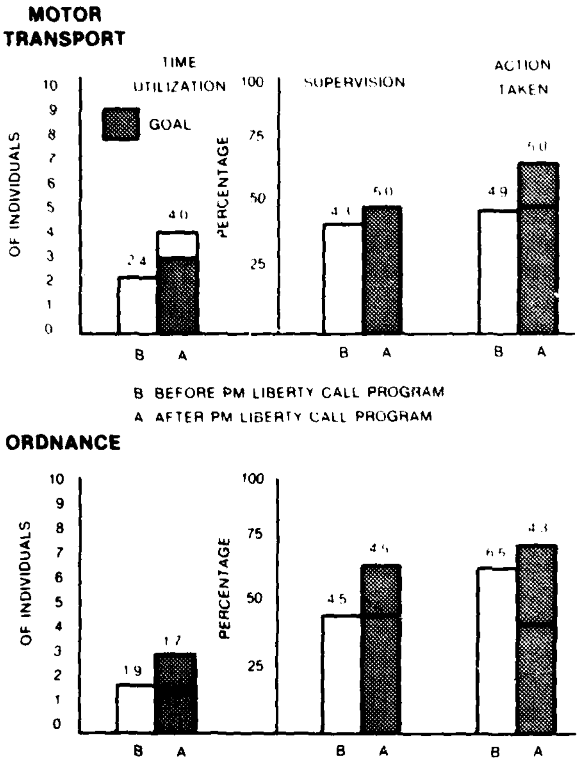
Results

Mixed Performance Results

The effects of the PM Liberty Call Program were mixed. Initially, the Program in the Motor Transport section was quite effective. Motor Transport personnel exceeded all PM goals by wide margins during the first four weeks. Time Utilization

Figure 1

Results in Motor Transport and Ordnance



doubled from an average of 2.4 Marines working during scheduled maintenance times to an average of 5.4 Marines, substantially exceeding the goal of 3.0. Likewise, the percentage of time a supervisor was present almost doubled from an average of 43 to 73 percent. Action taken on discrepancies also improved from an average of 49 to 82 percent of the items needing attention, well exceeding the goal of 67 percent. During this time, PM goals were met three of the four weeks and early liberty was awarded.

After the first month, however, performance in the Motor Transport section declined. By the end of the year performance had declined to such an extent that the goal was exceeded only slightly for Time Utilization and just barely attained for Supervision (Figure 1). Action Taken was affected the most, with personnel not even attaining the goal and performing not better overall after the program (M = 50 percent) than before (M = 49 percent).

In Ordnance, the PM Liberty Call Program did not produce any improvements whatsoever, as Figure 1 shows. For Time Utilization and Supervision, performance remained virtually the same. For Action Taken, performance actually declined over the course of the program.

Positive But Qualified Reactions

Many Marines noted that they liked the fact that the Program gave them "something to work for" and got "more people down here." However, many Marines regarded as insignificant the amount of time-off per week (10 to 15 minutes vs. the 30 to 60 planned) actually awarded when the weekly goals were attained. In addition, supervisors gradually lost interest in the Program, and this lack of support further diminished the Marines' motivation to do well.

Maintenance Takes a Back Seat

The lackluster results of the Program were not the result of a lack of qualified, committed, competent personnel, however. It was simply impossible for the Program, as it was conceived and implemented, to overcome the priority placed on more measurable, nonmaintenance commitments.

The way in which priorities are arranged in this environment makes it extremely difficult to conduct maintenance properly. It is not going too far to say that higher-level personnel indirectly encourage unit personnel to ignore maintenance needs in the press of more measurable commitments. No individual, regardless of how committed, could unearth maintenance from its lower priority status. Even if unit personnel wanted to show how additional commitments impede maintenance, they have no way of documenting the negative effects of this imbalance.

Also, while most persons in charge readily paid

lip service to the importance of preventive maintenance, they were not particularly displeased with the quality of maintenance being accomplished, given the time and resources available. This attitude is based primarily on a misperception. For example, when asked to estimate the time spent and action taken in the area of maintenance, supervisory estimates were frequently higher than warranted on the basis of the information we collected.

Finally, because no direct measures exist for PM performance and the evidence of maintenance neglect is hidden and often delayed, maintenance inevitably takes a back seat (one requiring repair, probably) to more visible commitments.

To illustrate: All personnel readily acknowledged the importance of maintenance. One Marine simply noted that "if the trucks are not up, you can't go anywhere." However, the priority given to maintenance in actual practices was very different. When asked what priority is placed on PM compared to other areas, personnel in Motor Transport (MT) and Ordnance (Ord) rated it as follows:

high 1 2 3 4 5 6 7 low
Ord MT

One Marine remarked, significantly, that he would rate PM a "2" on the training schedule but, because of the many other commitments, he would rate it a "5" in terms of actual practice. First echelon personnel point out that more emphasis was placed on other activities such as close order drill, field days, flu shots, dental appointments, and classes.

When maintenance was scheduled, it was assigned for a sizeable portion of the work week (15 hours on the average). However, entire weeks would go by during which none was scheduled. For a total of 16 weeks the Battery was primarily engaged in field firing exercises or preparing for a major inspection, so maintenance was not even scheduled. In addition scheduled maintenance activities were deleted during at least eight weeks and other activities were added on at least one day. The net result was that the maintenance schedule was left intact for less than half the weeks of the year (23 of 48).

To emphasize the major point: As the Marine Corps currently handles preventive maintenance, the problem is the crisis management, not the people.

As with faulty PM, the costs of this kind of crisis management are difficult to establish precisely. There is, unfortunately, only one certainty about crisis management: it will provide an ongoing cycle of crises to manage.

Can Anything Be Done?

If preventive maintenance is ever to be improved and sustained, a number of steps must be taken to overcome, or at least to counterbalance, the effects of this crisis management environment.

First, the status of maintenance should be upgraded by making it more visible. Feedback about PM performance should be provided each week to persons doing the work and to their supervisors. Furthermore, this information should be forwarded to middle and upper management on a monthly and quarterly basis, respectively. By improving the adequacy and frequency of PM performance, management can make more knowledgeable decisions and persons in charge can better motivate their subordinates.

Second, further clarifications should be made about the criteria first echelon personnel should use when detecting deficiencies. Forms such as the Weekly PM Checklists that are used assessing the condition of equipment should be revised so that the standards are clear. This will result in more accurate information about vehicle condition and more effective follow-up activities.

Third, improvements should be made in the communication between and within the various subunits. Because successful follow-through often entails a three-step process from first echelon to second echelon to the supply system, for instance, specific procedures and timetables should be established. This would encourage the transmission of correct and timely information.

Fourth, there should be continued emphasis on supervisory personnel. Because of the hidden and delayed nature of maintenance, performance and effects, supervisors must have specific guidelines about how to direct, monitor, and motivate personnel. When managerial procedures are clarified, supervisory personnel can be held accountable not only for the results their subordinates produce but also for their own actions.

Fifth, PM performance measures should continue to reflect whether maintenance has been done. However, the emphasis should be on whether the work got done rather than when (e.g., during scheduled maintenance).

Sixth, positive consequences should continue to be provided. If maintenance performance can be directly, frequently and objectively assessed, then feedback alone should be a sufficient and effective motivator.

Is There Any Hope?

A refined PM Program, based on the above recommendations, is currently being implemented and tested in another heavy artillery Battery. Thus far, the Program looks quite promising, showing substantial improvements in maintenance performance and an increased priority placed on maintenance.

ACKNOWLEDGEMENTS

For their invaluable assistance and encouragement on this project, the author is greatly indebted to: Dr. Robert Hayles and Dr. Bert King of the Office of Naval Research and Colonel Bernard Clark, USMC, (Ret.) formerly of ONR; to Lieutenant Colonel Kenneth Noland, USMC, (Ret.) formerly of the 2nd Marine Division; to Major Alex Chacto, USMC, (Ret.), Major Donald Herman, USMC, (Ret.); and to Dr. Patricia Penn and Dr. Anthony DeCurtis of the Georgia Institute of Technology. ■

Dr. Judith L. Komaki was a Principle Research Scientist at the Engineering Experiment Station, Georgia Institute of Technology, when she performed this research. In fall 1982 she will be an Associate Professor of Psychological Sciences at Purdue University. A member of the American Psychological Association, Dr. Komaki has published extensively in the area of work motivation.

research notes

Progress in Piezoelectric Polymers

Certain polymers have been found to exhibit piezoelectric (and pyroelectric) activity and have the advantage that they can be formed into films and shapes which are impractical for ceramic piezoelectrics. It is the goal of research in this area to understand the piezoelectric phenomenon in polymers and to find the means for making practicable their use in naval acoustic sensors and detectors. Dr. Martin Broadhurst has made significant progress in understanding piezoelectric behavior in polymers. Some recent research highlights from his group at the National Bureau of Standards are outlined below.

A suitable model for piezoelectricity in polymers has been developed. The mechanism for piezoelectric and pyroelectric response in amorphous and crystalline polymers is similar. It is the change in polarization (dipole moment per unit volume) due primarily to the thermally or mechanically induced volume changes of the sample (secondary piezoelectricity and pyroelectricity) rather than dipole moment changes which are commonly responsible for piezo- and pyroelectric response in ceramics. In semi-crystalline polymers such as poly(vinylidene)fluoride, PVF_2, dipole alignment is established by electric field induced rotation of molecules in individual crystals with stabilization by crystal packing energy. A cooperative six-site model has been developed for beta-phase PVF_2 which accounts for this ferroelectric behavior. Results from the model mimic the essential features of polarization, infrared and x-ray hysteresis data. Refinements of the model are needed to explain the observation that removal of the poling electric field results in some loss in crystal alignment.

The gamma-phase of PVF_2 has been prepared by depositing an additive (2% siloxane-oxyalkylene copolymer, L-520) from ethanol onto alpha-phase PVF_2 powder and heating (1°C/min) to 176°C. Films of alpha and gamma phases were subjected to the same poling conditions and the piezoelectric and pyroelectric responses were measured. The much larger response from gamma phase for all electric fields less than 1.25 MV/cm confirms that this is a polar crystal phase. The value of 1.3 nC/cm^2K for pyroelectric coefficient after poling for 10^3 seconds at 80° and 1 MV/cm is almost the same as that reported for unoriented beta phase obtained by pressure quenching and poled at the same field for one hour at 23°C. For values of electric field 750 kV/cm and greater, the alpha phase undergoes the electric field induced phase transition to a polar form so that at 1.25 MV/cm the responses from alpha and gamma phase films are comparable. Because of the field-induced phase transition of alpha phase, there seems to be no practical advantage for promoting the formation of gamma phase unless one must be confined to low poling fields.

An interesting feature related to the poling process concerns the effect of orientation on polymer conductivity. It is not generally possible to pole PVF^2 at fields higher than 1.25 MV/cm because of electrical breakdown. In the course of this investigation it was discovered that simply orienting the polymer film reduces electrical conductivity by more than a factor of 100. An improvement in electrical breakdown strength is indicated but not fully quantified at this time. This phenomenon will be examined more fully during the next year. Another area of emphasis will be the development and application of a digitalized thermal pulse technique which will yield information on the polarization distribution in the polymer films. Resolution of these data to about one-tenth film thickness has recently been demonstrated. This amount of detail in the charge and/or polarization distribution is expected to be of great value in directing the development of models for non-uniform field distribution during the early stages of poling. ■

(Kenneth J. Wynne, ONR)

Computer Language Development

Through its contract with Professor Noah Prywes at the University of Pennsylvania, the Office of Naval Research is making a pioneer contribution to the development of nonprocedural computer languages—languages whose special focus is their use of equations rather than procedures to specify the requirements of a machine program. Dr. Prywes' work in this arena, combined with his research interest in automated programming, has been evidenced in his design of a language called MODEL. A justification for MODEL, as for nonprocedural languages in general, rests on the argument that they are both easier to learn and to use; that, in fact, they facilitate the programming of computers by non-computer specialists. Prywes, working with Professor Lawrence Klein of the Wharton School, is convinced of the superiority of MODEL vs. conventional procedural languages for such problem domains as economic modelling, accounting, and business statistics.

Interest in the nonprocedural languages approach within the Navy is seen in such recent events as: (1) Assistant Secretary of the Navy for Financial Management constituting an advisory board to investigate the utility of nonprocedural languages to Navy accounting needs, and (2) Naval Data Automation Command lending a data base and committing personnel resources to the MODEL research activity. Beyond the claimed advantages in the business world domain, Professor N. Chomsky, Massachusetts Institute of Technology, has argued implicitly that nonprocedural grammars capture significant generalizations about language structure that could not be captured easily by a procedure for generating sentences from meanings, or a procedure for performing parsing operations. Chomsky also states that nonprocedural representations of linguistic rules are easier to arrive at. Another interesting fact about such linguistic rules is that nonprocedural statements apply equally well to different tasks, such as spelling spoken words or pronouncing spellings. For procedures to attain the same generality, it is necessary to make the procedures conditional on the task to be done; the equivalent procedure is thus more complex in this sense.

Responding to the Assistant Secretary of the Navy, Financial Management interests, ONR is sponsoring an experiment to permit some direct comparisons between procedural and nonprocedural languages for economic/accounting applications. The first experiment will utilize University of Pennsylvania faculty and students as its subjects. Future plans include the use of Navy managers and programmers as subjects.

While there are programming devices that are unique to procedures or equations, there are many features that are common to both; examples include:

- Use of variables as shorthand for complex expressions (intermediate variables);
- Reference to the arguments of a function in its name or definition (e.g., f(x,y)) for keeping track of what each function depends on;
- Subscripts—when variables are classified by successive integers that in essence serve as arguments of functions;
- Specification of the range or conditions of application;
- Nested functions (e.g., sums of sums).

Further, the literature of programming languages hypothesizes on features unique either to procedures or equations.

Those features identified as unique to procedural approaches include:

- Ordering of operations—the essential idea of all procedures;
- Iteration—repetition of a sequence of operations;
- Subroutine—hierarchical operations with repeated elements;
- Recursion—problem reducible to simple problem of same form;
- Use of "memory" and "files" to store data.

Those features put forward as the special characteristic of equation based languages include:

- Eliminates requirement for ordering operations;
- Specification of inequalities (or, more generally, truth conditions that constrain the value of an expression without determining it);
- Use of more than one unknown in a single equation (as in simultaneous equations);
- Use of functions of unknowns instead of unknowns themselves.

ONR continues to be concerned with the general problem of software measurement or metrics. Lessons learned from the described test effort—lessons in terms of the design and conduct of language comparison studies—will be applied to the DOD-wide concern with evaluating Ada (the proposed new standard language for tactical computing). ■

(Marvin Denicoff, ONR)

LMED

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