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STUDIES AND APPLICATION OF ADAPTIVE DECISION AIDING IN ANTI-SUBMARINE WARFARE

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NOTES

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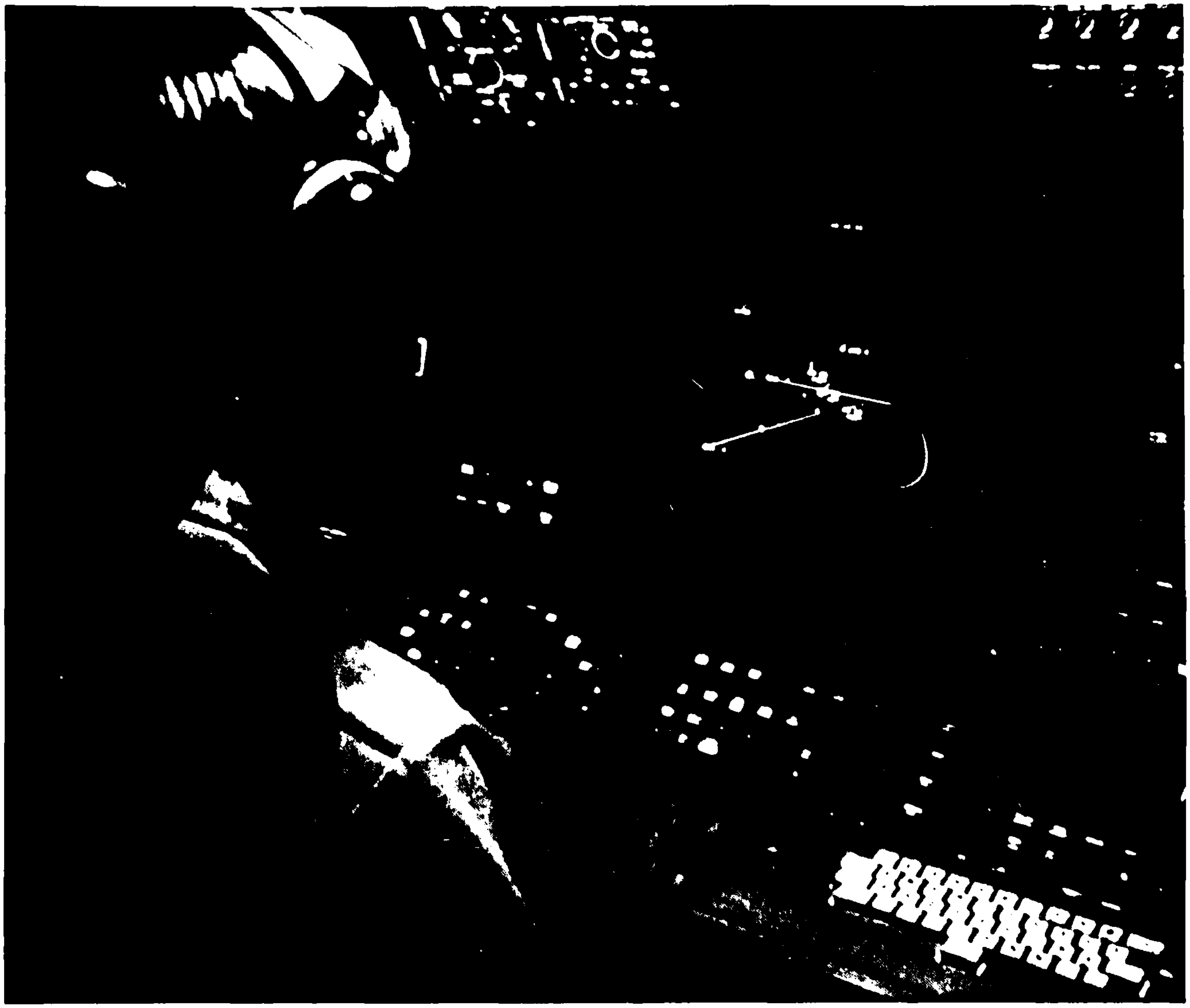

TABLE OF CONTENTS

TABLE OF CONTENTS (Cont.)

1. INTRODUCTION

1.1 Summary

This report presents the results of a research and development program designed to apply and demonstrate adaptive decision aiding in anti-submarine warfare (ASW). The work reported here on an adaptive decision aid (ADA) is designed to improve the decision aiding effectiveness of the Tactical Coordination Officer (TACCO) aboard the Navy P-3C aircraft as he deploys his ASW sensors. The ADA consists of a number of aiding functions that are performed during actual TACCO decision making, and are specifically suited to decision aiding in the rapid-response, repetitive, and dynamic environment characteristic of tactical ASW situations. The ADA has been integrated into existing P-3C simulators at the Naval Air Development Center (NADC) and successfully demonstrated in a submarine tracking scenario.

The development program has three main accomplishments:

(1) The transfer of advanced decision aiding from a laboratory research environment to a specific test environment which simulates ASW system application.

(2) The demonstration of the feasibility of the decision aid by implementing and integrating it into the existing ASW decision task structure and existing simulation computer hardware.

(3) The construction of an evaluation tool that can be used to analyze an individual's decision performance and determine the potential payoff and acceptance of decision aids in operational settings.

The ADA is designed to utilize adaptive techniques that "capture" and model decision making strategies and, then, recommend future actions based on both objective criteria and the subjective values implicit in the learned strategies. The heart of the aid is an adaptive pattern recognition model that is used to learn decision strategies and a multi-attribute model that is used to generate action recommendations.

The specific function of the aid is to provide decision (i.e., action) recommendations to a decision maker faced with time critical, repetitive, and dynamic decision making tasks. In the case of TACCO decision making, the decision involves tactical allocation of acoustic ASW sensors. These allocation decisions are particularly difficult due to the many factors (attributes) that must be taken into consideration (i.e., mission objectives, ocean conditions and weather, aircraft resources, time, etc.). The basic philosophy of the aid is to make sensor allocation recommendations to a TACCO that are based on his own preferences with respect to these attributes. The ADA is adaptive in the sense that it adjusts its internal parameters dynamically based on real-time observations of a TACCO's decision strategies. This technique has been proven successful in laboratory experiments and has resulted in a marked increase in decision making performance (Freedy, et al, 1976).

1.2 Problem Statement and Approach

Tactical operations are becoming increasingly sensitive to the quality of decision making. Large stakes rest on the ability of a tactical decision maker to request and process volumes of information, and to make rapid and effective decisions. Often, the decisions are made sequentially, and the consequences of each are likely to affect subsequent future decisions.

The human decision maker (DM) generally performs sub-optimally under conditions such as those found in tactical decision making. Cognitive limitations on memory, attention and processing, and biases and inconsistencies in aggregating information typify his behavior.

This problem is of particular importance in airborne tactical ASW operations which are characterized by the usual decision processes of data gathering, data evaluation, and resource allocation but further complicated by unusually severe time constraints. Given the complexity of the general ASW decision task, the often severe time constraints associated with airborne operations, and the inherent limitations of human capabilities, the airborne ASW decision maker is normally taxed to his fullest. Consequently, airborne ASW effectiveness depends heavily on individual decision making performance. Thus the proper application of advanced tools for computer decision aiding promises to have a significant impact on mission performance by improving tactical decision performance. Specifically, computer aiding can improve performance by allocating the decision functions between man and machine in a way which optimizes their respective strengths. Computer techniques can also provide computational aids for analyzing and formatting relevant decision data, as well as providing criteria for evaluation of alternatives and eventual selection of a course of action.

Moreover, in a dynamic setting where the complex future consequences of any current decision must be considered, the computer is an ideal observer and responder to a human during his decision making process. This type of interactive participation requires of course, a computer capable of adapting to changing task requirements and operator needs. Also, the often subjective nature of real world decisions requires some form of an adaptive model of the human decision maker, in order to determine his preferences and goals.

Perceptronics has developed and demonstrated, under previous ARPA and ONR* support, a computerized decision aiding system. The system combines major concepts of decision theory with adaptive computer technology to provide fast, real-time decision aiding of the type required in tactical situations. For example, the following decision aids are provided:

(1) Real-time probability aggregation and report generation of exact outcome.

(2) Recommendation of the optimum alternative in any decision situation.

(3) Decision quality feedback.

Experimental evidence from simulated tasks closely paralleling ASW tactical operations has indicated that this form of a decision aid (1) significantly improves operator consistency, (2) significantly improves decision quality, (3) reduces inter-operator variability, and (4) increases decision rate. The decision system is described in detail in Section 2.3.

In addition, preliminary analysis of the tactical ASW decision environment has shown that the aid is well-suited to provide an experimental testbed for decision aiding research. In particular, the aiding program is ideal -- in terms of structure and development state -- to supplement the new computer systems being introduced into ASW operations. The system can provide high fidelity simulations which (1) permit evaluation of numerous aiding approaches, (2) give valuable design inputs to hardware/software structures, and (3) have significant operation potential.

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1.3 System Overview

The adaptive decision aid (ADA) has been integrated into the Navy P-3C simulators designed to provide high fidelity ground simulation of the airborne Tactical Coordination Officer (TACCO) command and control console, and to train TACCO's and other P-3C crew members for airborne anti-submarine warfare (ASW) missions. In its current form the decision tasks that are associated with the P-3C crew can be categorized into three types: (1) deployment of sensors, (2) mission coordination, and (3) sensor data evaluation. The decision aiding function is designed to aid in sensor deployment decisions. Sensor deployment involves the allocation of sensor resources (such as sonobuoys) during the detection, localization, or other major ASW phases when sensor data is required. Deployment decisions by the TACCO are based on feedback data from previous sensor deployment, sensor data evaluations, sensor deployment standard operating procedures, sensor resource availability, and a desire to achieve optimal sensor responses.

The ADA program aids the TACCO in making sensor pattern deployment decisions by displaying certain kinds of information on the TACCO's CRT screen. Specifically, the following major aiding functions are provided:

(1) Recommendation of the three best sonobuoy pattern configurations and the number of sonobuoys to be deployed in each.

(2) Display of data values for the four key attributes that characterize each recommended pattern.

(3) Recommendation of the optimal deployment location for the best of the three patterns recommended. (If the TACCO

elects either of the other two recommended patterns the optimal location for it replaces the optimal location of the "best" pattern).

The recommendation of the three best sonobuoy patterns is based on the adaptive modeling algorithm which has learned the TACCO's values by "observing" the actual patterns chosen by the TACCO for particular situations. The characteristic "attributes" of the patterns are descriptors that aid the TACCO in making his pattern selection. The four attributes currently available describe most of the factors taken into consideration by the TACCO. They are:

(1) Detection Index (DI) - A measure of the probability of detection associated with the pattern.

(2) Coverage Area (CA) - A relative measure of the projected ocean area covered by each pattern.

(3) Uncertainty reduction (UR) - The amount of reduction of uncertainty in the submarine location provided by the pattern.

(4) Resource Conservation (RC) - The effect on aircraft sonobuoy resources of deploying the pattern.

These attribute values are displayed to the TACCO along with the pattern recommendations so that a rational acceptance or rejection of the recommendations can be made.

The final aid is a display of the optimal deployment location for the recommended patterns. This display appears on the TACCO multipurpose display as a location point with a well defined orientation mark. This information also aids the TACCO in selecting a sonobuoy pattern for deployment (see Figure 2-3 which illustrates this display).

Once the TACCO has accepted or rejected the ADA pattern recommendations, the adaptive aiding system modifies its internal utilities so that they reflect the TACCO's pattern preferences in terms of the four major attributes. In this way, a new pattern recommendation can be generated on the next deployment cycle which is closer to the TACCO's current deployment strategy. After a short time, the model will converge, capturing the TACCO's strategies and aiding him accordingly.

1.4 Empirical Evaluation

Preliminary evaluations have been completed with the ADA system in order to (1) evaluate the type of control display necessary for effective aiding, (2) identify required changes and system improvements, (3) verify system operation, (4) demonstrate the operational system to experienced TACCO's, and (5) obtain preliminary data regarding system acceptance with an evaluation of system potential.

The results of the preliminary evaluation have shown that the decision strategy of a TACCO can actually be observed and learned by the ADA system and sensor deployment recommendations can be effectively generated by the system. Adequate response time was obtained and acceptable system adaptability to changes in TACCO strategies was achieved.

Moreover, the system was demonstrated to five current TACCO instructors who were given questionnaires asking for their estimation about the system potential. In general, the majority of the TACCOs were in agreement that the computer aid would help in several ways. In particular, they all felt that their job would be made easier and more effective overall.

They felt the system would standardize performance and reduce variability among operators in selecting sensor patterns, especially in situations where untrained TACCOs are involved. They also felt that the ADA could provide a recommendation which could be based on more experienced TACCOs or, at least, help to improve their own choices since they would be provided with an optimal model.

With respect to the interaction between the system, and the TACCO, they felt that the procedure for probability entry and other required information is adequate as currently implemented.

While the ADA system shows substantial potential for TACCO aiding, further engineering evaluation and controlled experimental studies should be performed in order to refine the system and move it to full operational implementation. In particular, it is important to refine and fine-tune system functions so as to assure that the ADA is completely compatible with the TACCO task and accurately fits the decision situation in such a way that its performance improvement and impact is maximal. In addition, it is important to experimentally measure the effectiveness of the system in terms of its expected real-world mission payoff and set up a basis for further functional expansion and transfer to fleetwide operational applications. Such experiments are also required in order to provide guidelines for an expanded application in other airborne ASW mission phases as well as examine its feasibility for shipboard ASW operations.

2. BACKGROUND

2.1 Adaptive Decision Aiding Methodology

The ADA system concept is based on an early development of adaptive decision aiding methodology ADDAM (Freedy, et al, 1973). The adaptive methods involve the on-line acquisition of operator decision strategies by computer observation of his behavior. This dynamic modeling is capable of in-task observation of operator decisions made in response to real world probability data. The decision maker's value structure is then computationally inferred through a pattern recognition algorithm, and used as an input to a decision recommendation program. The resulting behavioral model and aid have the advantages of (1) functioning operationally in actual tactical circumstances, (2) adapting to changing task requirements and operator capabilities, and (3) requiring minimal programming complexity. These techniques use pattern recognition or learning algorithms to estimate behavioral parameters. The ensuing models are then used to train, replace or evaluate the operator. The current work extends this field by placing the operator in a real time interaction with his model. The system both descriptively models and prescriptively aids the operator.

Because the decision model is adaptive, model-based decision aiding establishes a complex synergistic relationship between the operator and the aid. The system adapts to the human operator's pattern of behavior and, in turn, provides decision aiding which may cause the human to modify his behavior. In a sense, the decision maker is provided with a tool that refines his behavior. Rather than confronting each decision anew, and depending on often fallible processes of recall, recognition, problem structuring, and evaluation, the operator uses logically derived recommendations to guide and condition his responses.

The current ADA model is based on an underlying expected utility (EU) model which assumes that the operator chooses that action whose expected (probability weighted) utility of outcome, is highest (Krantz, Luce, Suppes, and Tversky, 1971). EU models, of course, are not a panacea for structuring decision models. Lichtenstein and Slovic (1971) argue that descriptive models must take cognitive factors into account; Luce and Suppes (1965) question the use of deterministically maximized choices rather than stochastic choices; and Wendt (1970), and Coombs and Pruitt (1960), contend that the EU model should be modified to account for preferences in variance of outcome. In general, though, the usefulness of EU models is conceded in situations where the number of choices is low and the decision maker can relate to all attributes in terms of probabilities (Goodman, Saltzman, Edwards, and Drantz, 1971). Also, the EU models have the advantage of modeling both descriptive and normative (optimal) behavior, unlike most of the heuristic-based models (Wendt, 1973).

2.1.1 ADA Theoretical Structure. The ADA Support System is composed of a combination of complementary elements -- a set of *utility aggregation* programs, a dynamic model for tracking operator values for outcomes, and a strategy recommendation algorithm. Each of these aiding subsystems has a major role in augmenting the human functions of problem formulation, analysis, resolution, and evaluation.

Utility Estimation and Aggregation. Of prime concern are the considerations of perceived gains associated with the decision outcomes. Occasionally, objective values in terms of dollars, ship-equivalents or other external criteria can be used as criteria for choice. The situation must be exhaustively quantified to justify this type of calculation. For instance, a strategy for action selection based on objective criteria such as speed, accuracy, or expected value may be relatively easy to derive when system objectives, behavior, and environmental conditions are completely specified. Given the immediate utilities of obtaining the

possible outcomes and given the costs of the consequences, the decision choice with the highest operator utility can be selected. Objective performance criteria for the immediate task in most man-machine systems, however, are not well defined, or are only indirectly related to long-term system goals. This indeterminacy is particularly evident in systems operating in dynamic environments, where the results of earlier decisions affect later decisions. Such systems may rely heavily on the operator's subjective evaluation of the situation at hand, and the decisions should be based on measurable subjective preferences (utilities) of the operator.

Numerous techniques are available for assessment of the operator's utilities, ranging from ad hoc procedures to completely axiomatic analysis. The simplest techniques entail eliciting direct expressions of preference along qualitative or quantitative scales. Fishburn (1967) lists more than a dozen such direct methods. Other techniques of utility assessment include the decomposition of complex decisions into hypothetical lotteries, and the use of multivariate methods to analyze large numbers of binary preference expressions to determine underlying factors (Kneppreth, Gustafson, Johnson, and Leifer, 1974).

A major practical limitation to the application of decision theory is the complexity of utility assessment techniques. Most applications require a two-step process. The first step is to assess the decision maker's (DM) utilities, and the second is to apply them to the decision problem. Because it is not feasible to reassess utilities frequently in repetitive tasks, it is assumed that they remain static during this application. Such an assumption might be valid for a "one-shot" decision. However, there is no reason to assume that the DM's utilities remain static during the performance of multi-stage decision

tasks. Nor is it reasonable to assume that they remain the same when the context changes from that of a laboratory context to the real world task.

The technique developed in ADA for dynamic utility estimation circumvents many of these problems. Dynamic estimation uses the principle of a trainable multi-category pattern classifier to "learn" the operator's utilities for the outcomes of information acquisition decisions (Freedy, Weisbrod, and Weltman, 1973). Such an application of pattern classification techniques was first suggested by Slagle (1971), who pointed out that the utility function was an evaluation function which could be learned from a person's preferences. The adaptive technique assumes an expected utility maximization paradigm for modeling decision behavior, and uses a pattern recognition algorithm to successively adjust the model to fit observed decision behavior. The underlying maximum utility model assumes that the operator chooses that action whose utility of outcome is highest (Krantz, Luce, Suppes, and Tversky, 1971).

The advantages of the dynamic observation technique are as follows. (1) Utilities are estimated non-verbally, without the need for a skilled analyst highly trained in utility estimation techniques. In fact, the decision maker need not be aware that his utilities are being assessed. Utilities can be estimated rapidly and the technique is not limited by the number of possible decision outcomes. (2) The utilities are measured on a common scale and are combinable. (3) The utility assessment technique responds to changes in values and the utilities are automatically validated by direct comparison with the decision maker's real world behavior.

Strategy Recommendation. Another major element of the ADA system, the strategy recommendation program, follows naturally from the

utility estimators. With these parameters defined it is a simple matter to recommend individually optimal decisions. The choice with the greatest utility is determined and displayed to the operator. The recommendations given are thus based on the operator's own apparent values, and are organized into a normative framework. A certain generality is present in the normative processing since the recommendations are not restricted to the identical circumstances of the observations used for training. Recurrent observations of the operator actions are necessary for estimation of parameters, but these determinations generalize to other circumstances of the same structure. This means that the requirements for successful strategy recommendations using the adaptive decision aid are (1) a complete set of known possible actions, (2) a repetitive decision environment, and (3) a set of relevant attributes of the decision situation that reflect the operator's preferences. It is only necessary to observe a small number of actual decisions to determine the correct utilities. These utilities then generalize to any circumstances within the scope of defined decision environments. These criteria are met in the P-3 decision environment.

2.1.2 Aiding Dynamics. The strategy recommendation algorithm closes a man/computer decision cycle or loop of considerable flexibility and dynamics. The extent of the aiding can be observed by examining the major decision processes of information acquisition and action selection. In the information acquisition task, the operator receives feedback of the data requested and of the costs of data acquisition. To achieve long-term success, he must ascertain what type of behavior led to maximum performance, a difficult task with probabilistically unreliable information sources. He must then use the data obtained to select timely actions and to evaluate his performance using sporadic or noisy performance feedback. This cycle repeats itself as information

is converted into action throughout tactical decision making, and because of the dynamic nature of these cycles, errors tend to compound.

Figure 2-1 illustrates the generalized form of the adaptive decision aiding system investigated by Perceptronics over the past five years. The upper part of the figure shows the usual control loop of the human decision maker. He or she processes decision information, presented on some form of display, and makes choices which both affect the decision environment and alter the information available for the next decision. The lower part of the figure shows the aiding system, resident in a digital computer that has as its input the same decision information available to the human operator, as well as the decisions made by the operator on the basis of that information. Using adaptive programs and normative decision criteria, the computer builds a decision model of the decision maker, and, by means of interactive display programs, provides the operator with *on-line recommendations based on* his own preferences and decision strategy. Later, for evaluation or training purposes, the computer provides a performance report, in which decision making effectiveness can be separated from the actual, probabilistic consequences of the decision.

The ADA support system was developed following the above concept. ADA consists of an adaptive decision model which continuously observes both the decision environment and the decision maker's behavior, learns his decision policy, and makes decision suggestions based on the apparent value of the alternatives to the decision maker. Currently, the modeling technique is based on the prediction of decision behavior according to a maximum utility strategy. In simple terms, utility is calculated by multiplying the subjective value (utility) of a decision outcome by its corresponding attribute levels. Previous investigators have shown that such a model is robust, and adequately represents human decision behavior in a variety of circumstances.

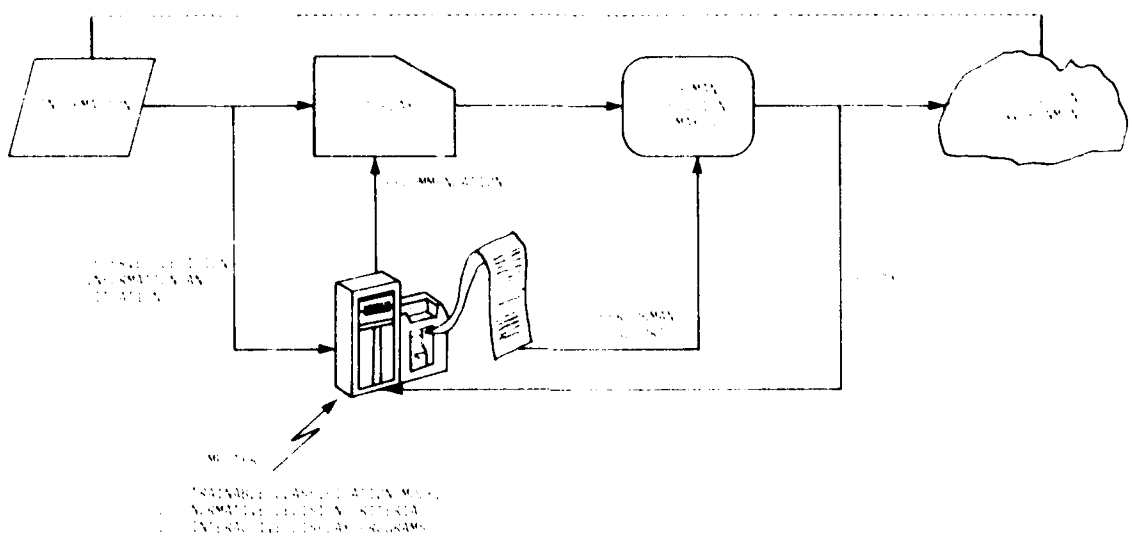

FIGURE 2-1. ADAPTIVE DECISION AIDING CONCEPT

The adaptiveness of the ADA system is realized through the use of a trainable multi-category pattern classifier that is used to estimate a decision maker's utilities or value structure. As the tactical decision maker performs his decision task, this on-line pattern classifier observes the choices among the various decision options. The classifier, using attribute values as inputs, attempts to classify these probability patterns by adjusting utility weights according to an adaptive error correcting algorithm. In this manner, the pattern classifier tracks an individual's decision making preferences and learns his utilities. Such an approach has a number of advantages compared to off-line utility estimation. Dynamic estimation observes and models actual behavior rather than responses to hypothetical decisions. It does not interrupt or intrude on the process of decision making; it responds to ongoing changes in task characteristics and operator needs.

2.2 The P-3C ASW Environment

2.2.1 Overview. This section describes the decision environment around which the aiding model is designed. The analysis is the result of an in-depth study of current Navy ASW operations. A typical peacetime anti-submarine warfare (ASW) mission consists of detecting and tracking an enemy submarine for as long as possible using a specially designed aircraft called the P-3C. The aircraft is equipped with different types of acoustic sonobuoy sensors and a computer system capable of processing tracking information.

The individual responsible for the major decisions aboard the aircraft is the Tactical Coordination Officer (TACCO, pronounced TACK-O). He must make decisions concerning (1) the course of the aircraft, (2) the pattern and type of sonobuoys to be dropped, and (3) the probable location of the submarine, etc. These decisions are part of the overall tasks of integration and evaluation of sensor information, management of sensor deployment, and (in wartime) management of weapon deployment.

2.2.2 The P-3C Aircraft. The Lockheed P-3C ASW aircraft (see Figure 2-2) contains three ASW sensor positions, a navigator position, and the TACCO station in addition to the pilot and co-pilot. The acoustic sensor stations are Sensor Station 1 (SS1) and Sensor Station 2 (SS2). These stations are capable of listening either actively or passively for submarine sounds (passive listening) or sonar echos (active listening) in the water. They are linked via radio with the sonobuoys deployed. Sensor Station 3 (SS3) is the Magnetic Anomaly Detector (MAD) station and the radar station.

The P-3C acts as the sensor and weapon platform from which the ASW mission is conducted. The aircraft carries a fixed number of sonobuoys and (in wartime) ASW weapons. The TACCO is in charge of the ASW search, detection, localization, and tracking (as well as attacking if in wartime) of hostile submarines. The navigator provides mission navigation information and acts as communications officer during the mission. The SS1, SS2, and SS3 operators are enlisted men who operate their respective sensor equipment.

2.2.3 The P-3C ASW Mission. The P-3C ASW mission consists of four phases: (1) search, (2) classification, (3) localization, and (4) attack (if in wartime) or tracking and gaining intelligence (if in peacetime). A mission begins with an intelligence report indicating that a submarine is in some area of the ocean. This initial area (and all subsequent areas in which the submarine is thought to be) is called an "area of probability". The ASW mission objective is to reduce this initial area of probability -- which starts out very large -- until it is small enough to successfully attack the submarine.

Once the preflight planning is completed, the P-3C departs for the initial area of probable submarine location, and the ASW mission begins. The search (and subsequent phases) are mostly acoustic. Visual and radar

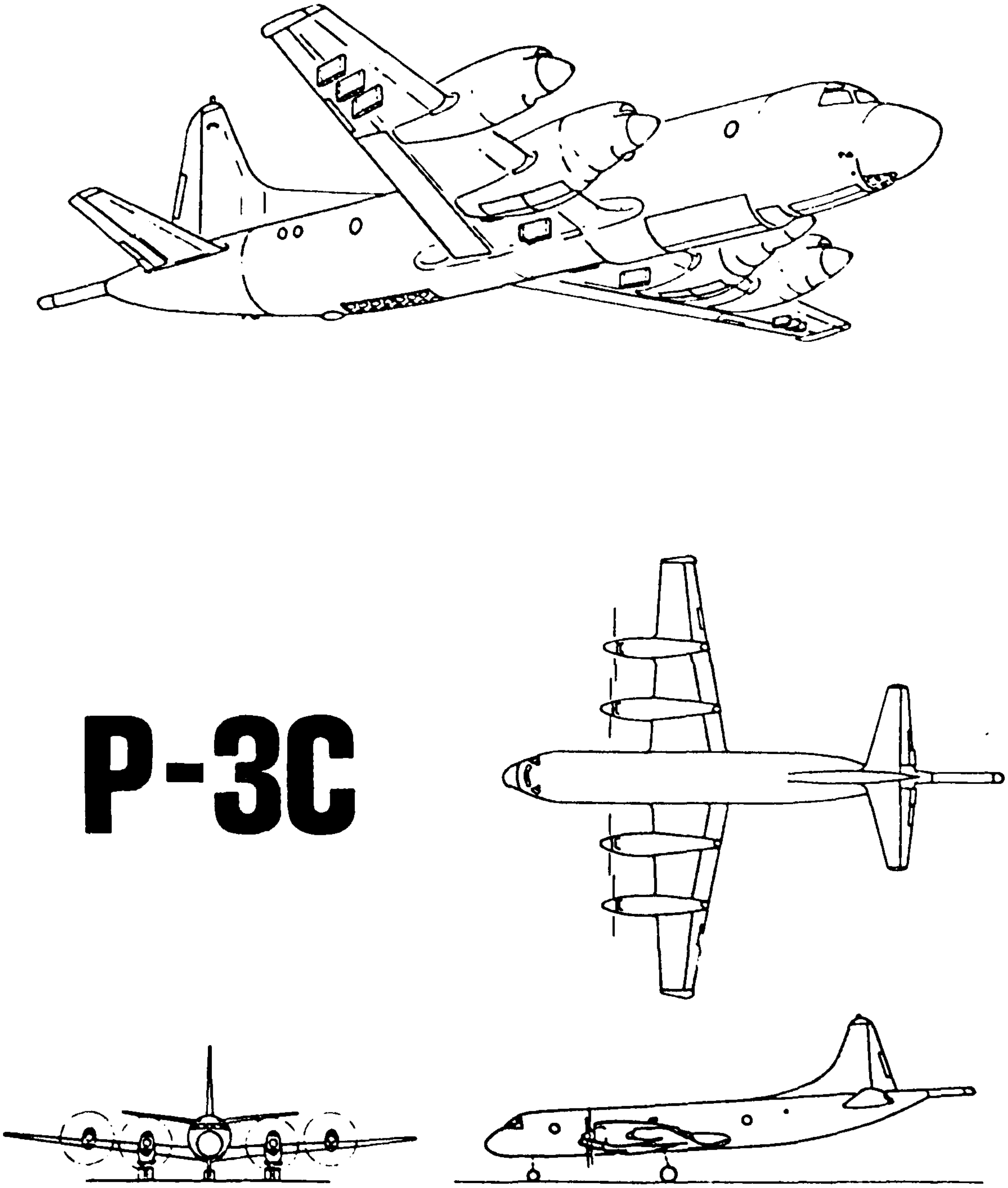

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FIGURE 2-2. THE P-3C AIRCRAFT

P-3C CREW STATIONS

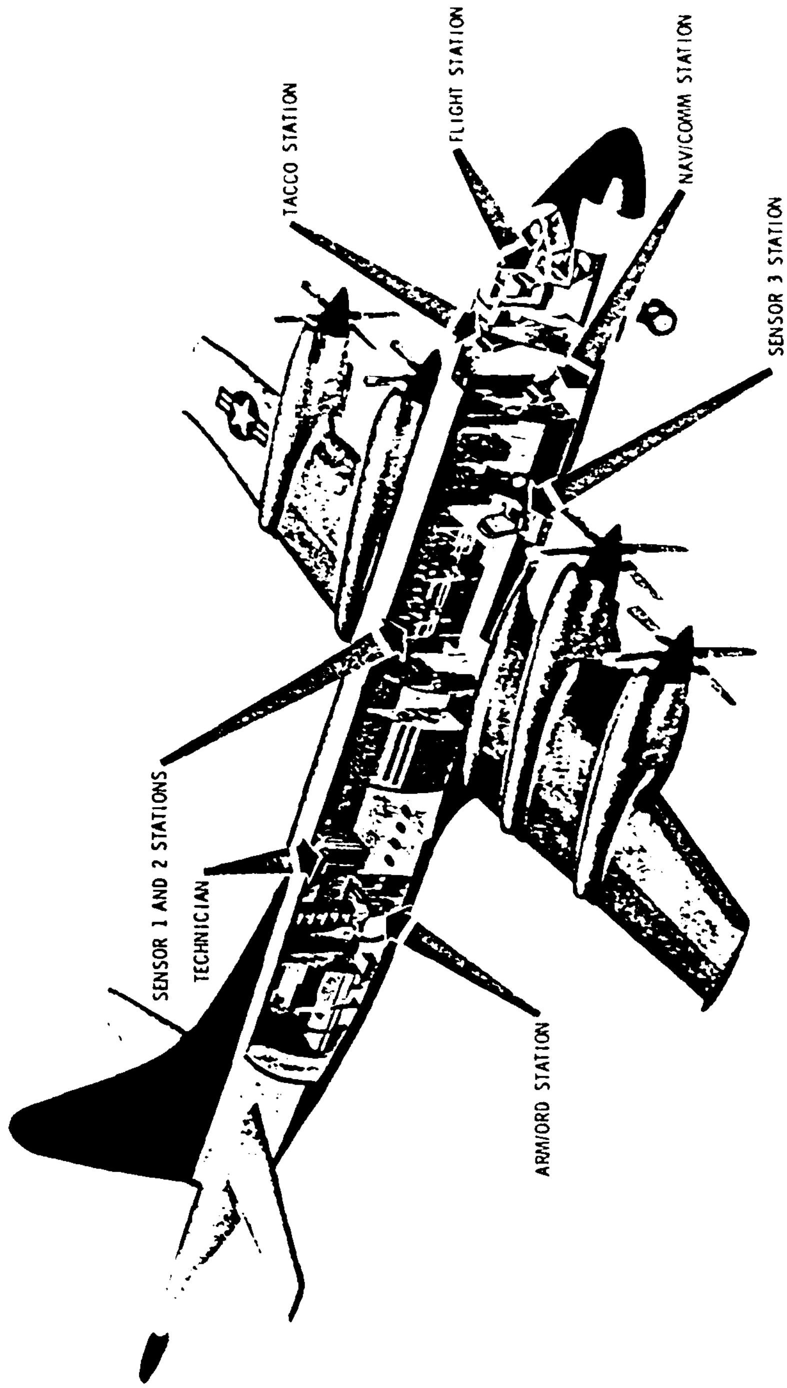

FIGURE 2-2. (Continued)

searches are infrequently used and MAD is used only in the tracking stages. (In the U.S. fleet, a training mission scenario is developed. U.S. submarines move into an area of probability and behave like enemy submarines. In the training center, fleet mission exercises are simulated by computer.) During a mission, there are three types of sonobuoys that can be used: (1) LOFAR which is a general passive, non-directional sonobuoy and not very expensive to use, (2) DIFAR which is passive and provides a bearing to a target but is about five times as expensive to use as LOFAR buoys, and (3) active sonobuoys. During a mission, the TACCO must decide how to place the sonobuoys and what type to use. He must consider how many of each type are on board, their lifetimes, depth settings, and quantities of each. After takeoff, most of the buoys cannot be changed. The settings decided upon in the preflight planning session are fixed in all but a few of the sonobuoys. Only these few can be changed in flight.

The mission really begins full force once an initial detection and classification occurs. The TACCO must then decide what course of action to take. What is the source of this sound? Must passive or active sonobuoys be used? (Often these questions are answered by fleet policies.) How is the target to be classified? These are examples of the types of questions that run through the TACCO's mind during the mission.

2.2.4 The TACCO Decision Task. Once the TACCO has dropped sonobuoys, some critical decisions must be made. He must decide what the sensor feedback or lack of it means. Conflicting feedback information can affect decisions. For example, items that influence the noise factor in sensor feedback are bottom bounce, conflicting bearings, loss of contact, (the submarine may hide behind undersea mountains, etc.), errors in sonobuoy bearings, and submarine course and speed changes. If a contact is lost in the passive search phase, one option is to go active (if permitted by fleet policies). In the localization and tracking phase, the critical

factor is the time to make a decision in addition to the "rightness" of the decision. An incorrect or slow decision can cause a contact to be lost.

During an ASW mission, the utility of the various sensors may change. For example, early in the search phase, LOFAR sonobuoys are very valuable as sensors. Later in the localization or tracking phases, LOFAR buoys are much less valuable and DIFAR buoys become the valued sensors. This clearly indicated that values are dynamic during an ASW mission, and suggests that adaptive decision aiding can be extremely helpful. Static decision aids cannot account for value changes as they occur, based on feedback patterns from the sensors in all the infinite variations that are possible.

2.2.5 Computational Aids. A sophisticated computational and information display system is available on the P-3C aircraft for the purpose of making the tasks of the TACCO more effective. The heart of the system is the TACCO display screen which summarizes sensor information and provides a visual mechanism for making decisions. Figure 3-2 shows a schematic of the TACCO station with the display screen in the center. The screen represents a designated area of the ocean around the current location of the aircraft. Information received from deployed acoustic sensors is initially entered into the computer system by the sensor operators at their individual stations. This information appears on the TACCO display screen as bearing lines emanating from previously indicated sensor drop point locations (see Figure 3-2). The TACCO must use the various computational and display aids provided to plan the allocation of new sensors so that contact with the submarine can be maintained as long as possible.

The primary computational aid is the "tracking bug" which predicts the most probable location of the submarine based on current information.

TACCO STATION ARRANGEMENT

(TYPICAL)

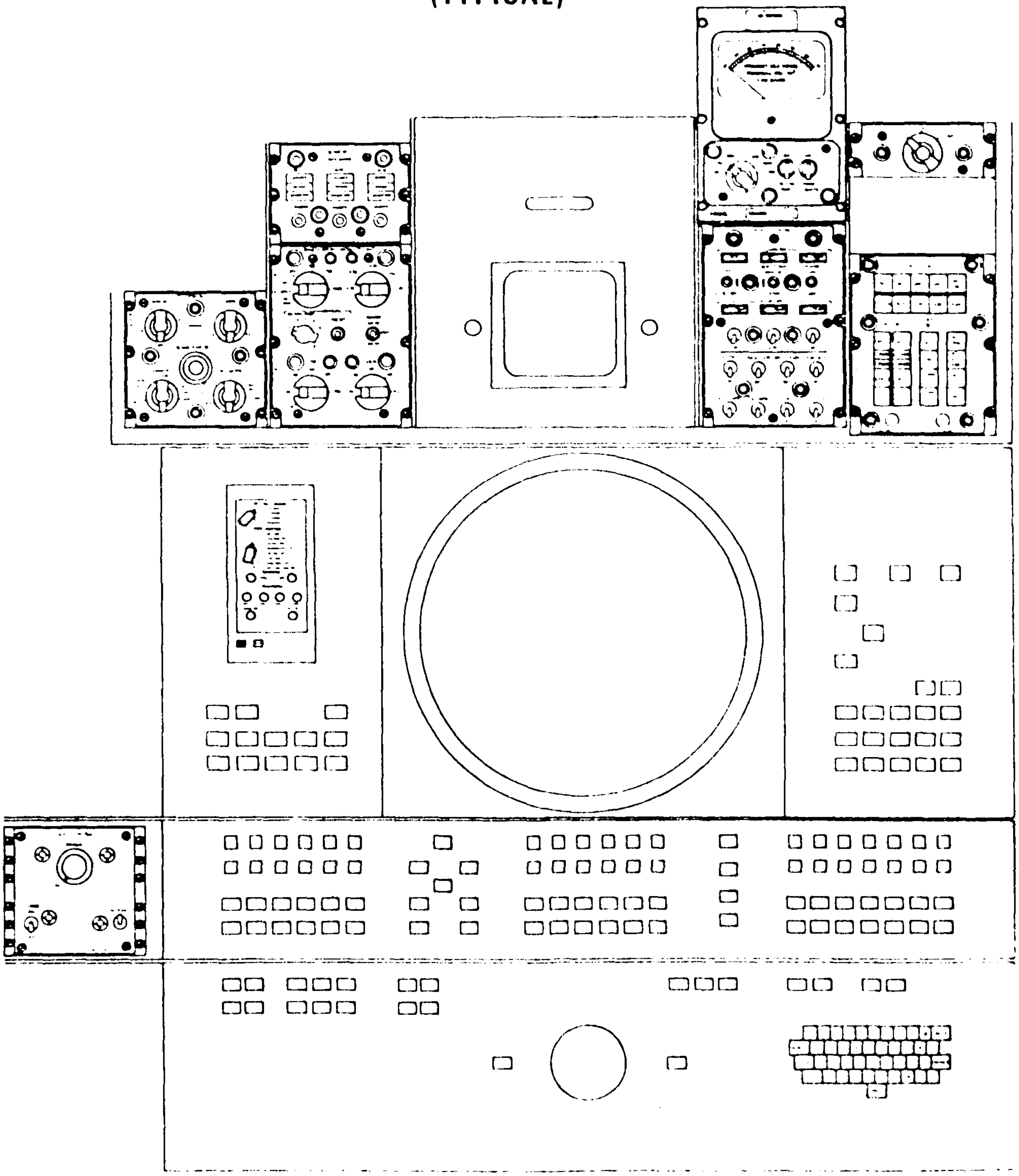

FIGURE 2-3. TACCO STATION

The tracking bug moves on the screen in real time and, consequently, is a continuously updated estimate. In order to produce the tracking bug, sensor information must be selected and entered by the TACCO. This is done by selecting promising intersections of bearing lines that appear on the screen and marking them for data entry. The intersections are called "fixes" and represent possible locations of the submarine based on pairs of sensor contacts. However, because of errors, it is rarely the case that all pairs of sensors will intersect at the same point. Thus, it is up to the TACCO to choose those fixes that seem most reliable and request a tracking bug based on this choice. Possible errors can arise from (1) sensor failure, (2) bearing errors, (3) signal reflections, and (4) operator errors, etc.

2.2.6 The P-3C Simulator Update System. The P-3C training simulator is an exact replica of the actual P-3C aircraft stations along with computer support for simulating the ASW mission environment. The latest additions to the simulator (called the "update" system) contain many improved data processing and display features. The following sections summarize a few of these features and their effect on the TACCO decision making task.

Probability Contour. A probability contour is a single ellipse that appears on the TACCO display screen. It is based on the probability of a submarine located at the intersection of two or more sensor bearings. The contour is not based solely on where the submarine itself is or could be. The contour is a combination of both sensor feedback probabilities and environmental conditions.

The Track-Fix. The update version has a built-in track-fix feature. In the previous version, the TACCO had to find the intersection of two bearing lines by himself visually. In the update system, the

intersection is found automatically by the computer, and shows an "x" on the TACCO display screen. He must then decide whether or not to enter this fix into the computer. After a series of two or three fixes are plotted, the computer generates the tracking bug.

Buoy Pattern Aids. After exchanging some information with the computer system and indicating some points on the TACCO display screen, the computer will automatically place the buoys in a pattern and designate the fly-to points for the pilot.

For example, in order to construct a "wedge" pattern, the TACCO is not required to enter data for each sonobuoy individually. He need only enter the parameters of the wedge, such as (1) anchor location, (2) spread angle, (3) orientation, (4) number of buoys, and (5) buoy spacing. These types of pattern aids also exist for the "barrier" pattern (straight line) and the "entrapment" pattern (circle).

2.3 The P-3C Adaptive Decision Aiding (ADA) Model.

2.3.1 Overview. The adaptive decision aiding methodology is intended to aid in the passive tracking phase of the ASW task. The phase can be described as a decision cycle shown in Figure 2-4. The TACCO receives information from previously deployed sensors, integrates and evaluates this information, makes his best estimate of the submarine motion, and decides where to optimally drop the next pattern of sensors so that the tracking be continued as long as possible with the least amount of resources expended. This cycle will be described in detail and the decisions to be made in the process will be indicated.

The cycle begins when the TACCO receives information from the previously deployed sensors (step A). The SENSO (sensor operator) -- who filters the raw information coming from the sensing devices -- presents

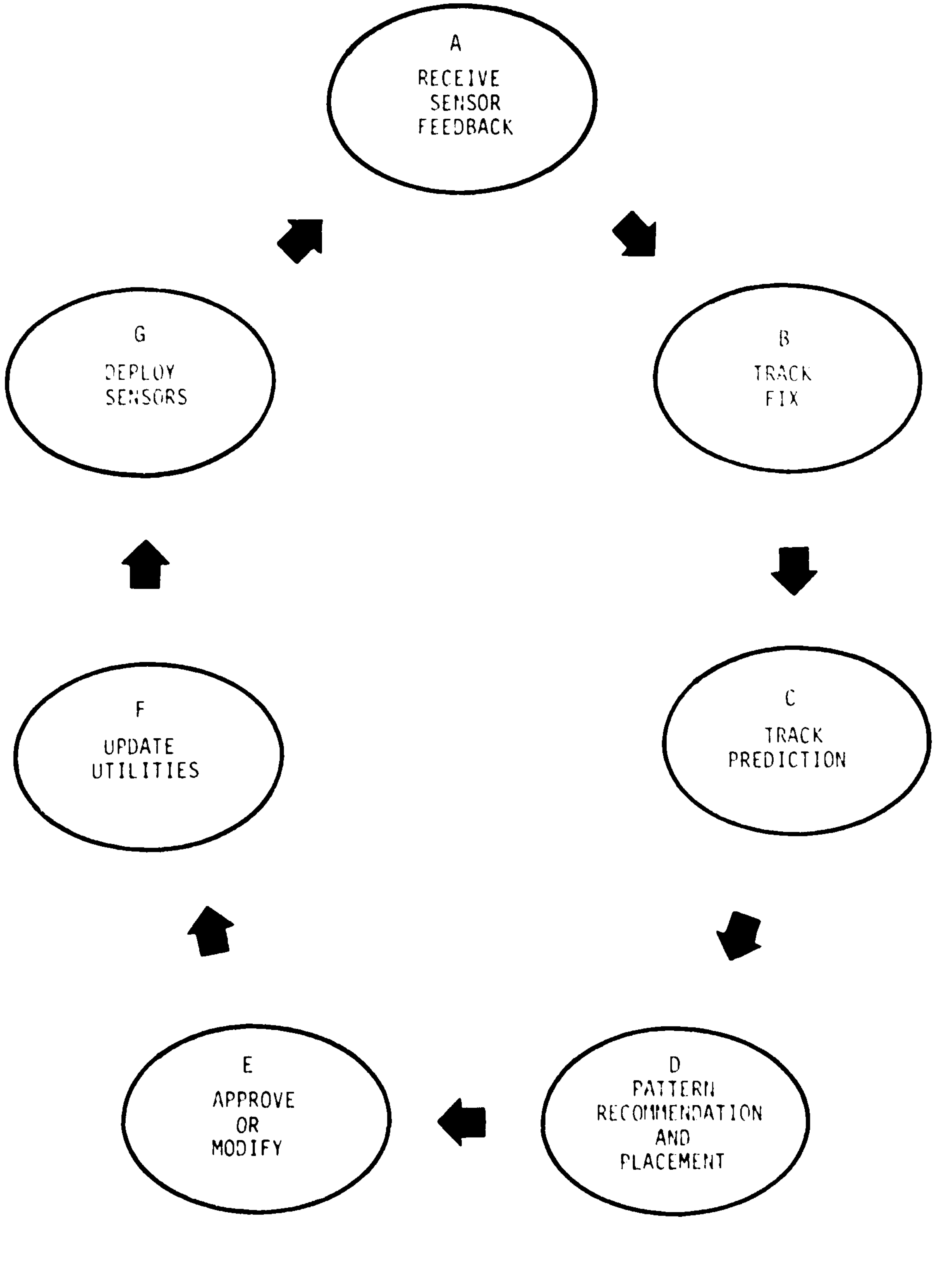

FIGURE 2-4. TACCO TASK CYCLE

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the submarine contact information as directed bearings and range circles on the TACCO's main data display screen.

The TACCO (step B) evaluates the incoming data and integrates his assessment of the situation by placing "fixes" at the bearing line intersections he believes to be true submarine locations. If he needs more information, he can prompt the SENSO to obtain more data from any sonobuoy in the water. The decisions he must make at this stage are: (1) which signal is a true submarine signal, (2) which intersection of bearing lines should be a designated fix, and (3) when to stop asking for more information and go to the next step.

In step C he makes, with the aid of the computer system, the best estimate of the current submarine location. This is given by the system as a probability distribution map which is calculated from the TACCO assessment of the tracks and from a priori statistical information on submarine behavior. It represents the probability that the submarine will be at various locations at any given time. The most likely location is displayed as a tracking "bug" and is updated in real time.

Step D comprises the decision aiding portion of the cycle. The adaptive decision aiding system calculates the optimal positions for each sensor pattern in the decision space and presents one of the patterns as a recommendation thus relieving the TACCO from this central decision. The recommendation is consistent via the adaptive model with (1) the past performance of the TACCO in similar situations, (2) the determined probability distribution of the projected submarine location, (3) the current environmental situation, and (4) the capabilities of the sensors used in the pattern. The recommendation appears on the screen as a text message indicating the pattern type and the number of buoys to be deployed. Upon request, the TACCO receives a display of the pattern superimposed on the map of the search area.

It is now incumbent upon the TACCO to approve or reject the recommended pattern (step E). If the TACCO rejects the pattern, he must allocate his own pattern of sensors manually. This manual allocation will, of course; follow established standard procedures as they now exist. In either case, the internal decision parameters are updated to reflect the TACCO's preferred strategy (step F).

The final step (G) of the decision task cycle is the actual deployment of sensors into the ocean. With the completion of this action, the cycle begins again when new contact information is received.

2.3.2 Decision Space. The decision space is the set of alternatives from which the TACCO has to make his choice. From all of the possible decisions confronting the TACCO in his submarine tracking task, the decision space has been reduced through detailed analysis and interviews with experienced TACCOs to two critical variables:

(1) Sensor pattern type
(2) Number of sensors in the pattern

The basic unit for sensor placement is a pattern. A basic experimental set of patterns has been developed for the decision aiding prototype system as one of the dimensions of the decision space. The basic pattern types which will be permitted in the decision aiding model are the following:

(1) Tri-Tac
(2) Barrier
(3) Wedge
(4) Entrapment

Figure 2-5 shows these patterns in graphical configurations. The black triangles represent sonobuoys. The small circle is a moving submarine entering the pattern group.

Tri-Tac. The Tri-Tac pattern is a group of three sonobuoys placed in an equilateral triangle configuration. One of the buoys is placed at the best current estimate of the submarine's location and the other two are placed so that the submarine will travel between them if it proceeds on a straight-line course. This pattern tends to be used early in the tracking phase of the mission, when the submarine location is known only through intelligence data, to get a quick initial estimate of the submarine's behavior without expending a great many sonobuoys.

Barrier. The Barrier pattern is a linear row of sonobuoys centered on the submarine's predicted path. The pattern usually consists of four or five buoys equally spaced and, on rare occasions, will contain as few as three or as many as eight. The pattern is perpendicular to the submarine's course so that the angles of contact bearings will be as orthogonal to each other as possible. The parameters required to specify a barrier pattern are (1) anchor-buoy location, (2) orientation angle, (3) number of buoys, and (4) buoy spacing. These parameters must be specified by the TACCO in addition to information about buoy type, depth setting, and lifetime.

Wedge. The Wedge pattern is normally used when the submarine's course and speed is known to a greater degree of accuracy. The wedge consists of from three to eight sonobuoys placed in two straight lines intersecting at an apex that is directly in the path of the submarine and oriented so that contacts will be as orthogonal as possible. The parameters required for wedge specification are as follows: (1) anchor (apex) location, (2) orientation angle, (3) wedge (acute) angle, (4) number of buoys, and (5) buoy spacing.

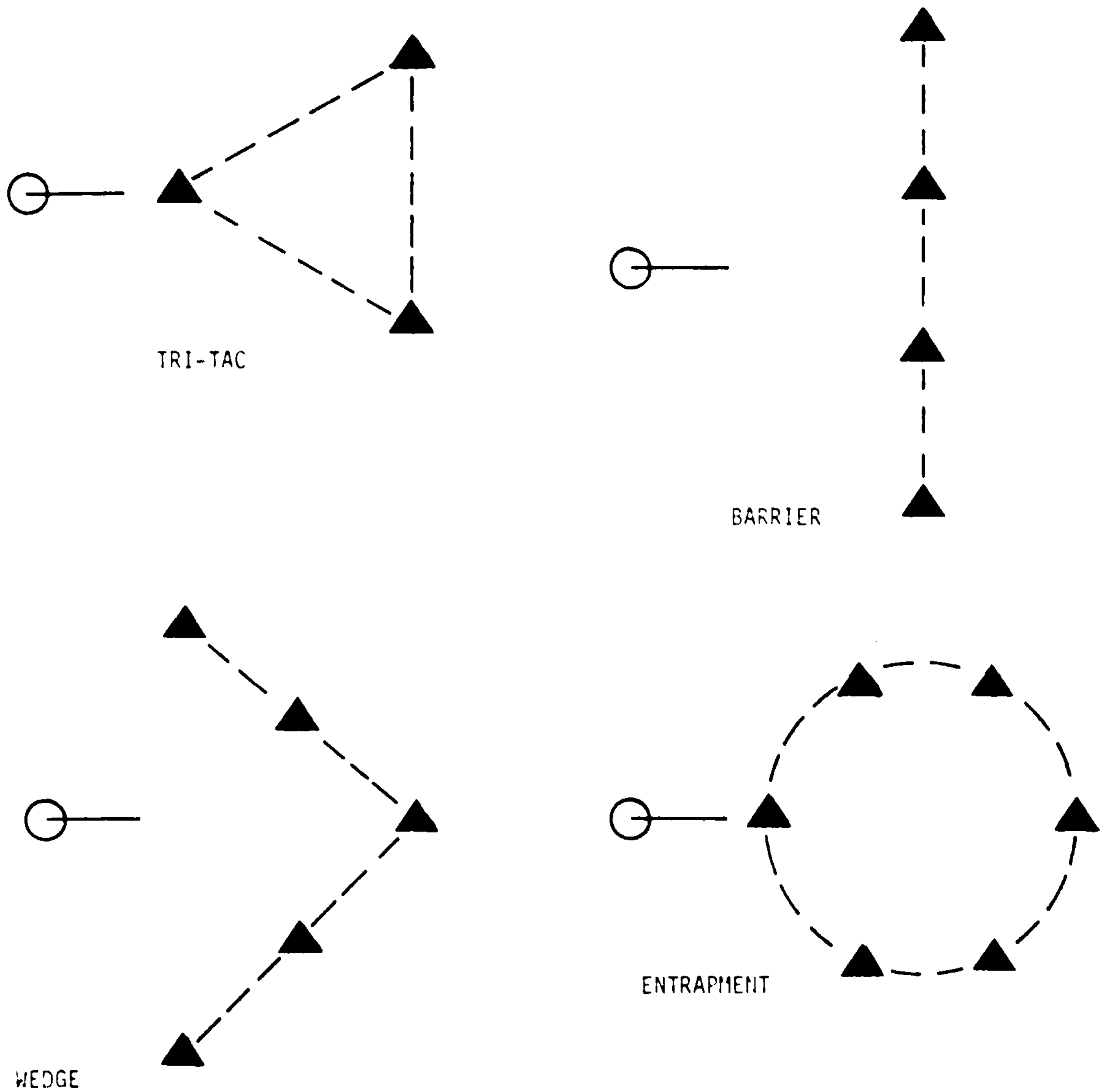

FIGURE 2-5. THE MAJOR PATTERN GROUPS

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Entrapment. The Entrapment pattern is a circle of sonobuoys placed so that the center of the circle and one of the sonobuoys are directly in the path of the submarine. The pattern may contain from four to eight sensors. The necessary parameters are (1) the center of the circle, (2) the radius, and (3) the number of buoys.

Pattern Characteristics. As described above, the decision space of sensor patterns has two major dimensions: (1) pattern type, and (2) number of buoys. The combination of 4 pattern types with a choice of 6 sensor densities (3 to 8) makes 24 possible decision alternatives in all. However, it is a unique characteristic of the tri-tac pattern that it always contains exactly three sonobuoys. Furthermore, the entrapment always contains more than three buoys. Thus, the total decision space consists of 18 distinct decision alternatives (see Figure 2-6). The decision aiding recommendations to the TACCO will be selected from this decision space. The sensor patterns have, of course, many more dimensions than pattern type and sensor density. Sonobuoy type, spacing, lifetime, and depth settings are all necessary information, but are not included in the decision recommendation space.

2.3.3 The Adaptive Utility Model. The P-3C decision aiding algorithm is based on the ADDAM decision model developed over the past three years at Perceptronics (Freedy, Davis, Steeb, Samet, and Gardiner, 1976). ADDAM decision aiding algorithms were modified to accommodate the increased complexity of the realistic P-3C ASW problem. Sensor patterns are used as the basic decision choice and critical factors such as sensor capabilities, sensor errors, tracking strategies, environmental conditions, and human factors were analyzed and incorporated into the developed algorithms (see Leal, et al, 1977).

PATTERN	NUMBER OF SONOBUOYS					
	3	4	5	6	7	8
Tri-Tac	*					
Barrier	*	*	*	*	*	*
Wedge	*	*	*	*	*	*
Entrapment (circle)		*	*	*	*	*

FIGURE 2-6. THE DECISION SPACE

The dynamic utility estimation used by ADA is based on a trainable pattern classifier. As the TACCO performs the decision tasks, the on-line utility estimator observes his choices among the 18 possible decision options available to him. His choice is viewed as a process of classifying patterns of "attributes" or characteristics which are calculated automatically from available information on sensor capabilities and current submarine location. The utility estimator then attempts to classify the patterns by using a linear aggregation utility rule as the discriminant function. These classifications are compared with the TACCO's decision and, whenever they are incorrect, an adaptive error-correcting training algorithm is used to adjust the utilities. In this manner, the utility estimator "tracks" the TACCO's decision making and "learns" his utilities. A more detailed discussion of the adaptive decision model and the training algorithm may be found in Freedy, Davis, Steeb, Samet, and Gardiner, 1976.

An important prerequisite to the application of decision aiding in the ASW environment is a realistic structuring of the decision process. In Figure 2-7, the decision task is presented as a decision structure. At the initial decision node on the left, the TACCO has to decide which sensor pattern P_i to deploy so that his task of continuous submarine tracking will be performed efficiently. This decision is based on maximization of utility. For each alternative choice there are four possible attributes:

(1) Detection Index (DI)
(2) Coverage Area (CA)
(3) Uncertainty Reduction (UR)
(4) Resource Conservation (RC)

Detection Index (DI). This is a measure of the likelihood that a given pattern will detect the submarine. It takes into account the

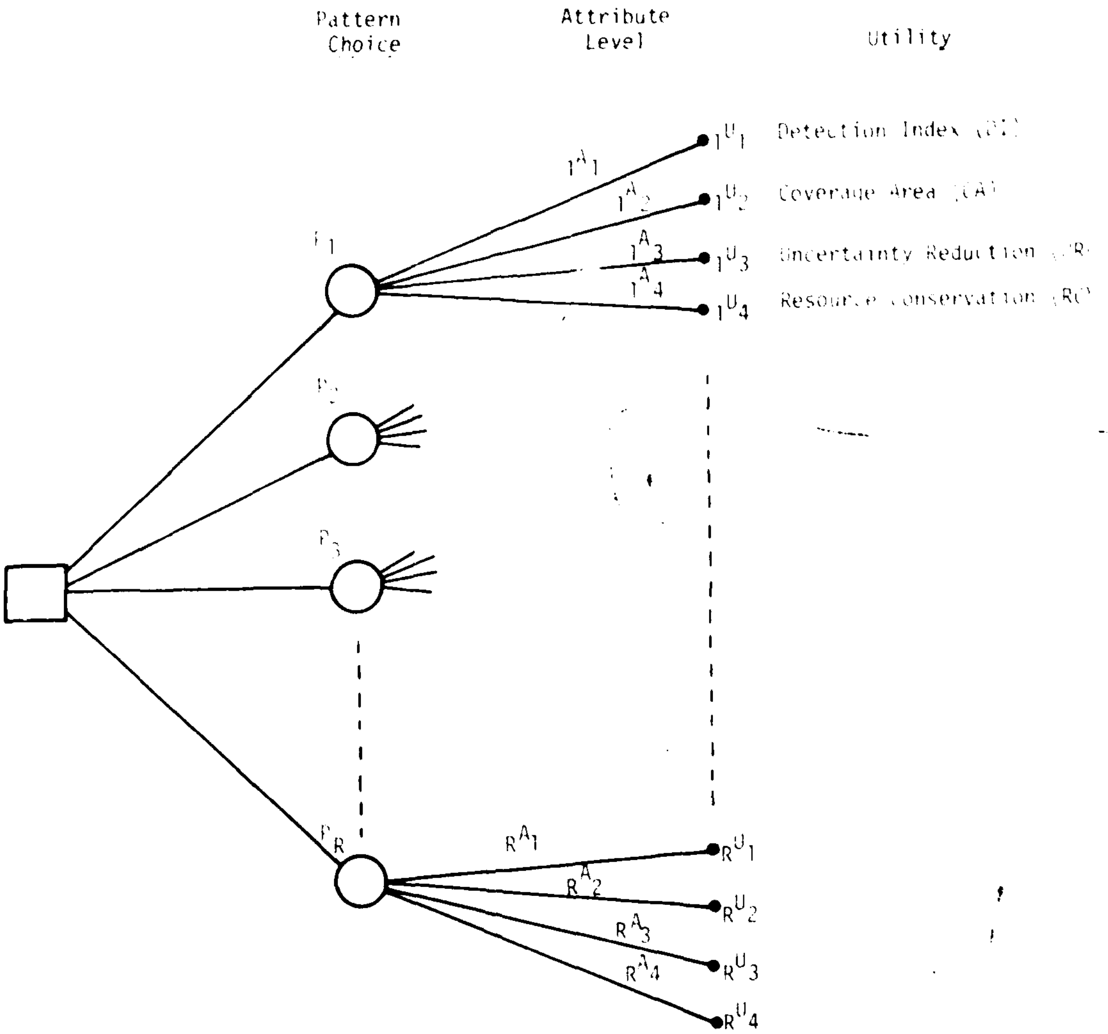

FIGURE 2-7. THE BASIC UTILITY DECISION MODEL

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pattern shape, the total number of passive sonobuoys in the pattern, the sonobuoy spacing as entered by the TACCO, the distance from the pattern to the current location of the submarine as predicted by each track, the track probabilities as entered by the TACCO, and a simplified distribution of submarine movement behavior. The final result is a number between 0 and 100 which is proportional to the probability of detection.

Uncertainty Reduction (UR). From the track probabilities entered by the TACCO, an information-theoretic measure can be obtained that describes the TACCO's overall uncertainty. The uncertainty reduction attribute is deduced for a given sonobuoy pattern. This value is converted to a measure between 0 and 100 that reflects reduction: the higher the value, the more the uncertainty will be reduced by that particular pattern.

Coverage Area (CA). The coverage area attribute is a relative measure of the projected area covered by each sonobuoy pattern. The smallest pattern (tri-tac) with a minimal sonobuoy spacing is assigned the value 0 and the largest pattern (barrier, 8 buoys) with maximal spacing is assigned 100. The others are valued accordingly. The attribute values will be altered by the sonobuoy spacing parameter entered by the TACCO.

Resource Conservation (RC). The number of passive sonobuoys still on board the P-3C aircraft is an important consideration when deciding which pattern to use and how many sonobuoys to drop. Through interviews with experienced TACCOs, it is clear that, ideally, the sonobuoys should be depleted in proportion to the length of time into the mission so that the last sonobuoys will be dropped into the water just before the mission is over. Thus, the sonobuoys and on-station time should end together. If the sonobuoys are depleted before the on-station time is exhausted,

valuable time is wasted which could have been used to track the submarine if more buoys were available. Conversely, if the on-station time expires before all sonobuoys have been used, the aircraft is forced to return to its base with less than optimal utilization of resources.

The resource conservation index is at its highest (100) when the number of sonobuoys on board is directly proportional to the time remaining in the mission. If sonobuoys are used too rapidly or too slowly, this index will decrease. The value displayed on the screen (see Figure 3-4) is, of course, that value which would result after the currently recommended pattern has been dropped.

Utilities are numbers which characterize a decision maker's value of a particular situation. They can be estimated only within the context of a particular decision model. In the P-3C model, the TACCO has an internal value associated with continuation of successful tracking of the enemy submarine and with conserving resources, etc. The expected utility model asserts that the TACCO will choose the alternative which will maximize his utility.

Initially, each alternative member of the decision space has a different vector of utilities associated with:

$$U_j = ({}_jU_1, {}_jU_2, {}_jU_3, {}_jU_4)$$

They represent the TACCO's personal preferences for each attribute of each pattern in the decision space and depend on various external variables such as weather conditions, submarine type, sea conditions, etc. In the P-3C model, the environmental variations are extracted from the adaptively varying part of the model. A different set of utilities is assigned to each combination of state variables. Once the state variations have been extracted, the decision tree can be simplified into

the form shown in Figure 2-8. Since all choices of patterns have the same set of attributes for a given state of the environment, the utility of each attribute does not depend on which sensor pattern is dropped to obtain it.

The expected utility equation for each pattern has a single set of utilities fo ...e various patterns which are weighed by the levels of their attributes. The model computes an aggregate multi-attribute utility (MAU) as a weighed sum of each attribute level A_i multiplied by the importance or utility of the attribute U_i. The calculated MAU of an alternative is used as the selection criterion.

2.3.4 <u>The Training Algorithm</u>. The training algorithm is a linear multi-category pattern classifier. Using a fractional correction factor, it traverses cyclically through the schematic diagram of Figure 2-9. On each trial, the model uses the previously calculated weights U_i for each attribute i to compute utility MAU_j for each pattern in the decision space.

The attribute levels ${}_jA_i$ are derived from previously known facts about the sensors, their reliability, coverage capability, etc. These levels are presented to the TACCO for analysis so that he will base his choice on the same information set. The model then assumes that the TACCO will always prefer to deploy the sensor pattern with the maximum MAU value. After the selection, the TACCO's choice and the model prediction are compared. If the prediction is correct, i.e., the TACCO chooses the pattern with the highest MAU in the model, no adjustments are made to the utility weights. However, if the TACCO chooses a sensor pattern with a MAU less than that of the predicted pattern, the model adjusts the utility weights using a correcting vector which is the difference between the attribute vector of the chosen pattern and that of the predicted one. In this manner, the utility estimator is "shifted"

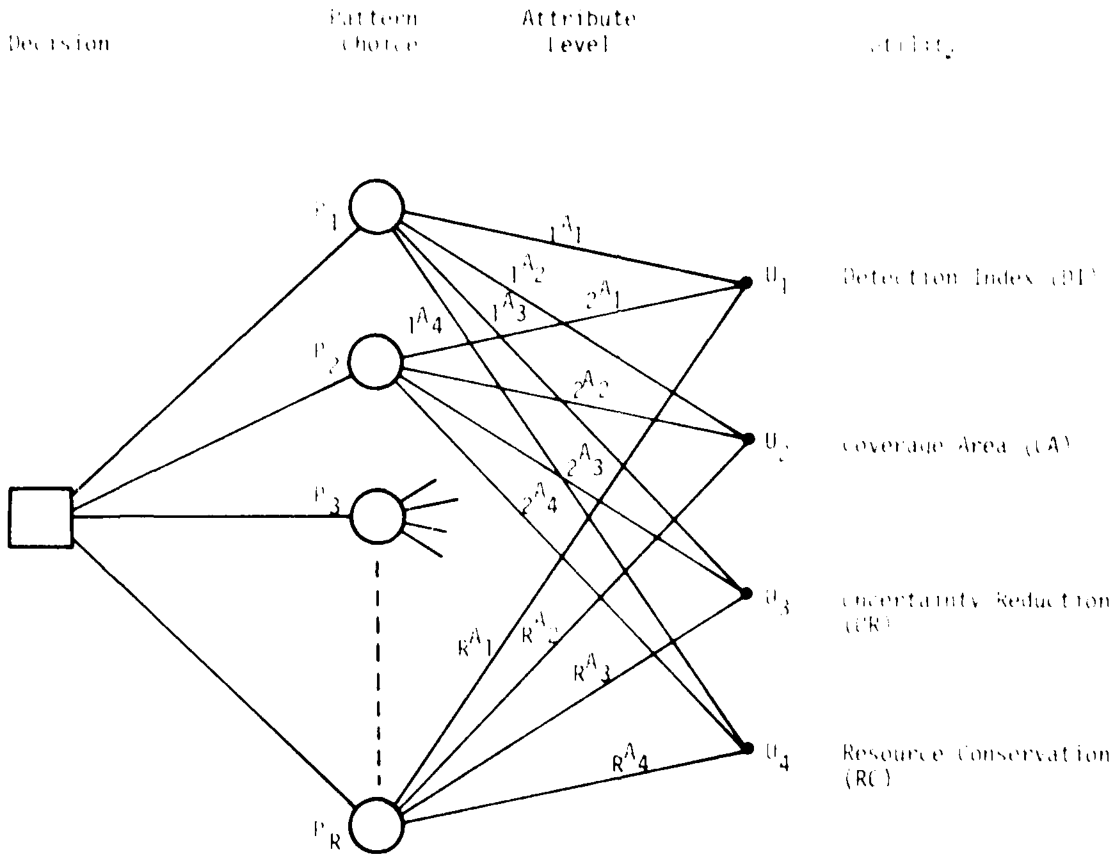

FIGURE 2-8. THE MODIFIED UTILITY MODEL

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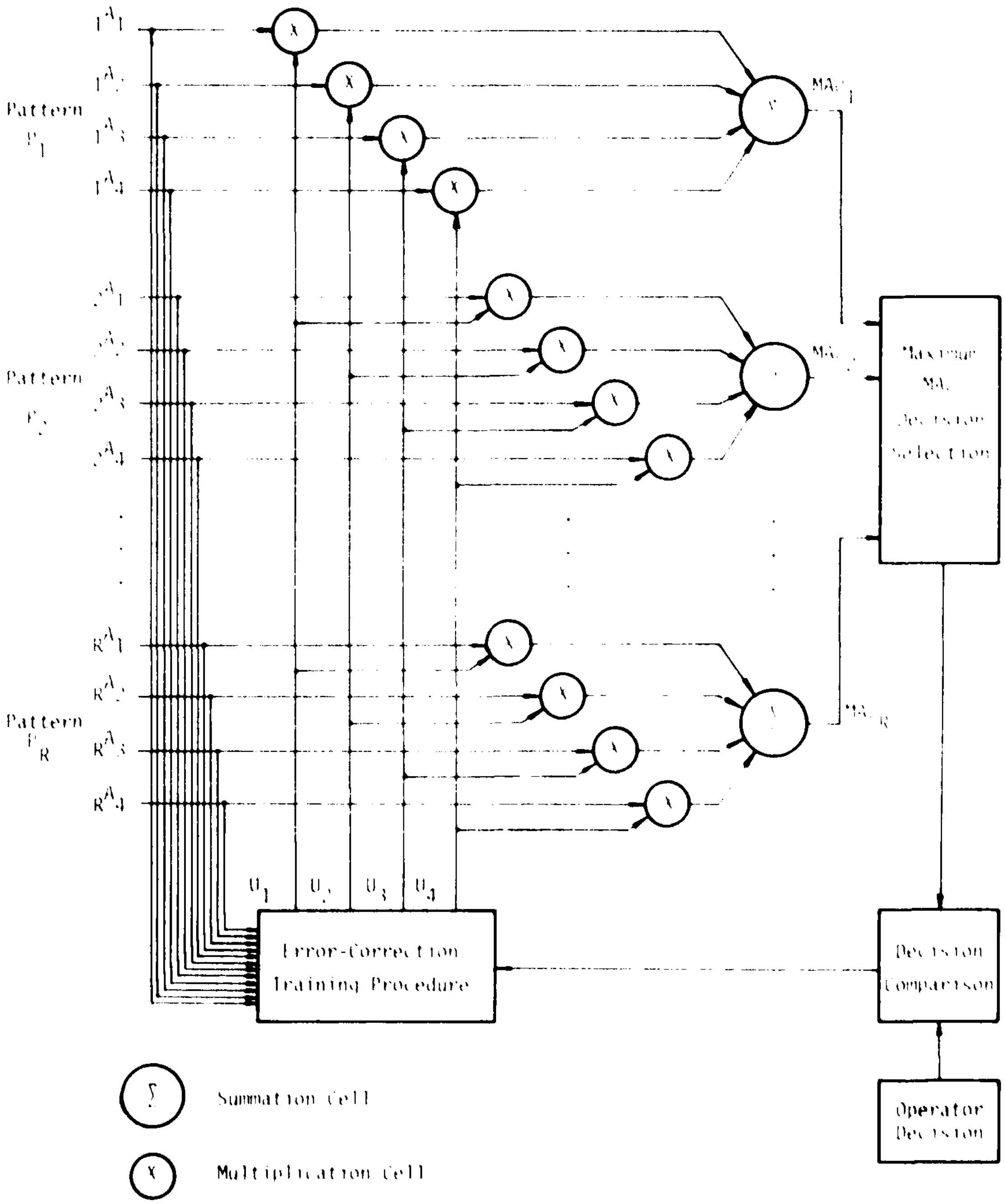


FIGURE 2-9. DECISION MODEL STRUCTURE

in the direction of the pattern that it "should" predict, and away from the pattern it did predict. The training rule used to adjust the utilities is illustrated in Figure 2-10. The correction factor λ controls the speed of convergence and is determined by experimentation. With a high λ, the utilities are adjusted more strongly, resulting in faster convergence to the operator's utilities. However, this also produces a higher sensitivity and thus, less stability.

The vector of utilities is initialized arbitrarily with all utilities equal to 1. It is guaranteed to converge to a solution vector if such a solution exists. That is, if the TACCO is behaving rationally, the model is guaranteed to find his internal values.

There are two phases in the training algorithm behavior which alternate according to a parameter θ representing the level of confidence the algorithm has about the TACCO's behavior. One is the "training phase" and the other is the "predictive phase". The effect of the two phases is that when θ is low, the system does not recommend a solution to the TACCO. When θ is high, it presents that element of the decision space with the maximum MAU as its recommendation.

The training phase takes place at the beginning of system use when the utilities have not yet had the chance to converge to a stable solution. The adaptive algorithm is bound, then, to make many prediction errors. In such times the system should not influence the TACCO by presenting erroneous predictions. Internally, the system performs the training process as given above. The training phase is defined by:

$$\theta \leq 0.7 \text{ where } \theta = \frac{n}{10}$$

where n is the number of correct prediction in the most recent 10 trials. When the confidence level goes above the specified threshold, the

Adjusted Weight $\hat{U}_i$		Previous Weight U_i		Adjusted Factor λ		Attribute Vector of Chosen Pattern ${}_cA_i$		Attribute Vector of Predicted Pattern ${}_pA_i$
$\hat{U}_1$	=	U_1	+	λ	$\circ$	$({}_cA_1$	-	${}_pA_1)$
$\hat{U}_2$	=	U_2	+	λ	$\circ$	$({}_cA_2$	-	${}_pA_2)$
$\hat{U}_3$	=	U_3	+	λ	$\circ$	$({}_cA_3$	-	${}_pA_3)$
$\hat{U}_4$	=	U_4	+	λ	$\circ$	$({}_cA_4$	-	${}_pA_4)$

FIGURE 2-10. THE TRAINING ALGORITHM

predictive phase begins. The system continues to apply the training algorithm but it also presents the TACCO with a recommendation: the pattern choice with the maximum value of MAU. The TACCO has the option to accept or reject this recommendation and the system will apply the error-correcting algorithm accordingly.

3. SYSTEM DESCRIPTION

3.1 Overview

Figure 3-1 shows the overall decision task cycle that the TACCO follows when allocating passive sonobuoys for submarine tracking. One of the most crucial decisions in this cycle is the type of sonobuoy pattern to be used given current tactical conditions and mission objectives. The ADA system provides the TACCO aiding for this particular decision.

The aiding is activated by the depression of a specific button on the TACCO's console. Thus, ADA must be voluntarily activated when needed. Once activated, the program time-shares with other active tactical activities. Thus, there is no interruption of normal procedures or activities. The aiding program may be cancelled at any time during its operation by depressing the same button. Since the utility training portion of the system is the last function performed in a cycle, a premature cancellation will not affect the model.

When activated, ADA begins its operation (Figure 3-1) by requesting an update on (1) the desired sensor spacing, (2) the desired time until pattern drop, and (3) an assessment of the TACCO's confidence level for each existing track. When this information has been entered, ADA displays a set of pattern recommendations along with the attribute information concerning each one. In addition, the optimal location for the best pattern is displayed on the screen.

With this information, the TACCO must decide whether to accept or reject the pattern recommendations. If he accepts, no further interaction with ADA is necessary. However, if he rejects the recommendation, he must indicate his pattern preference by entering this information as ADA

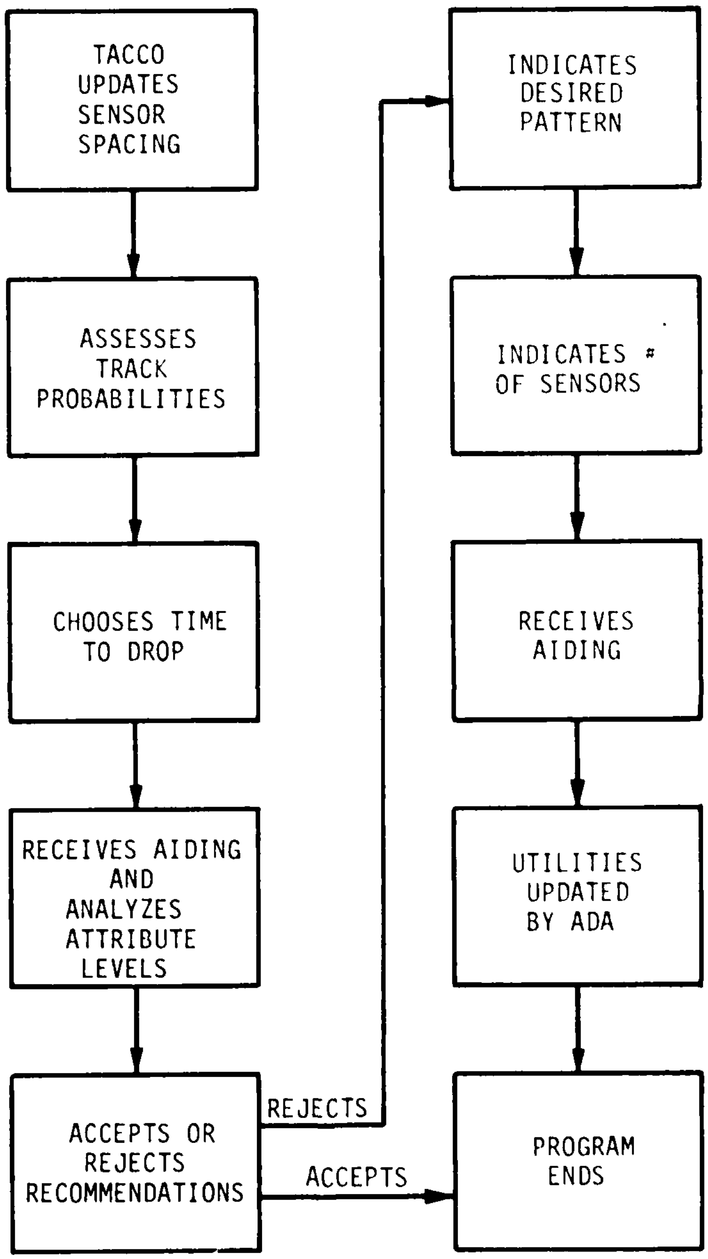


FIGURE 3-1
SYSTEM DESCRIPTION

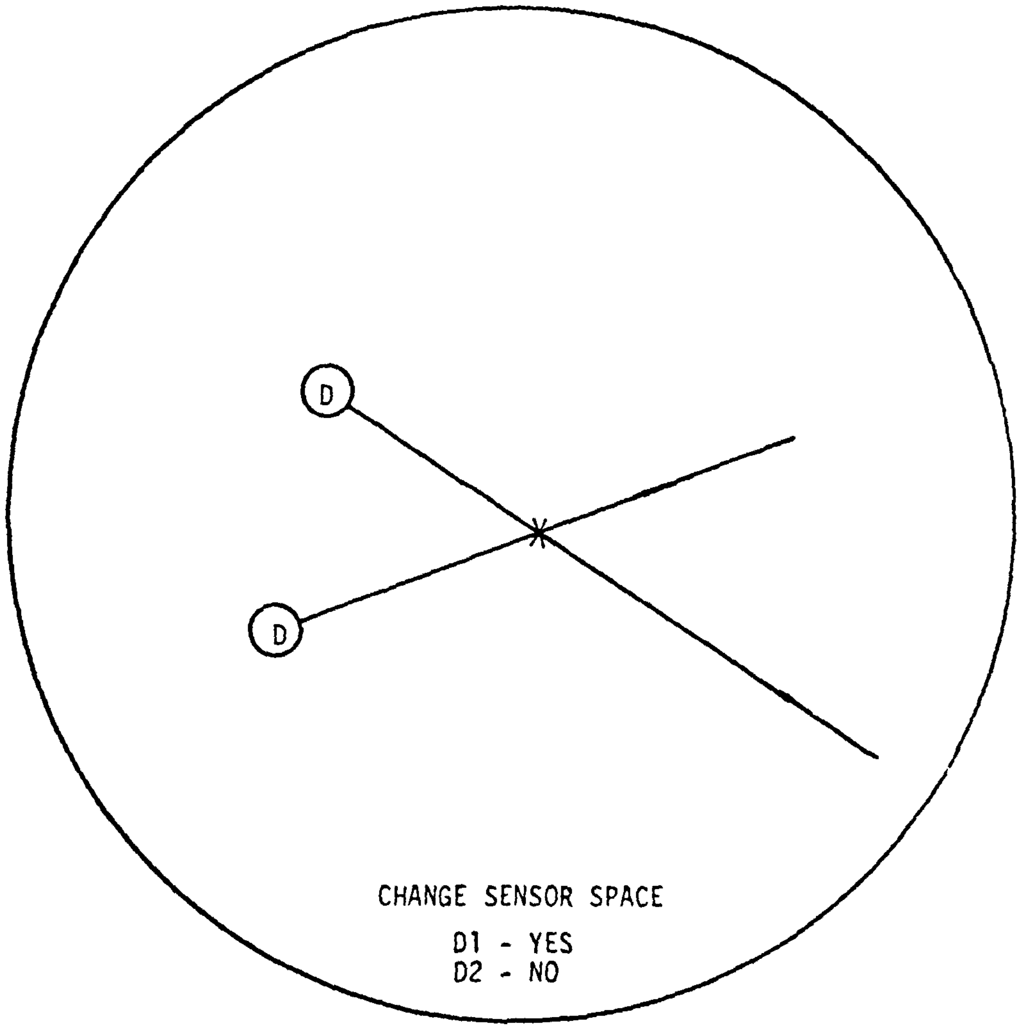
requests it. When this procedure is completed, ADA adapts its internal parameters to the TACCO's actual pattern selection and displays the optional location for it. The program is then ended.

3.2 Sensor Spacing

The "sensor spacing" refers to the desired distance between adjacent sensors in a particular sonobuoy pattern. This information is required to calculate the probability that the pattern will detect the submarine. At the beginning of the aiding program, ADA asks the TACCO if he wishes to change the current value for sensor spacing (see Figure 3-2). The standard decision buttons on the console marked D1 through D4 are used by this portion of the program as well as others. (TACCOs are currently familiar with the operation of these buttons as simple choice selections.) If the TACCO wishes to change the spacing, he indicates this by depressing D1, and then enters the new value on the keyboard. The spacing usually remains constant during a mission but may change due to weather changes, ocean temperature changes, etc.

3.3 Track Probabilities

Because incoming sensor data may have errors, the TACCO is able to cluster different sets of data points into predictions of the current location of the submarine. Each different set of data points constitutes a "track" and each track predicts a different submarine location. The TACCO has the capability of defining multiple tracks and monitoring all of them simultaneously. When the aiding program is operating, the TACCO is requested to input his preferences for tracks, specifying which are more likely to be the more accurate ones. Each track is thus assigned a numerical probability reflecting the TACCO's preferences (Figure 3-3). The probabilities are given in percent form from 0 to 100, entered on the keyboard console, and displayed immediately after entry for verification.


D
D
CHANGE SENSOR SPACE
D1 - YES
D2 - NO

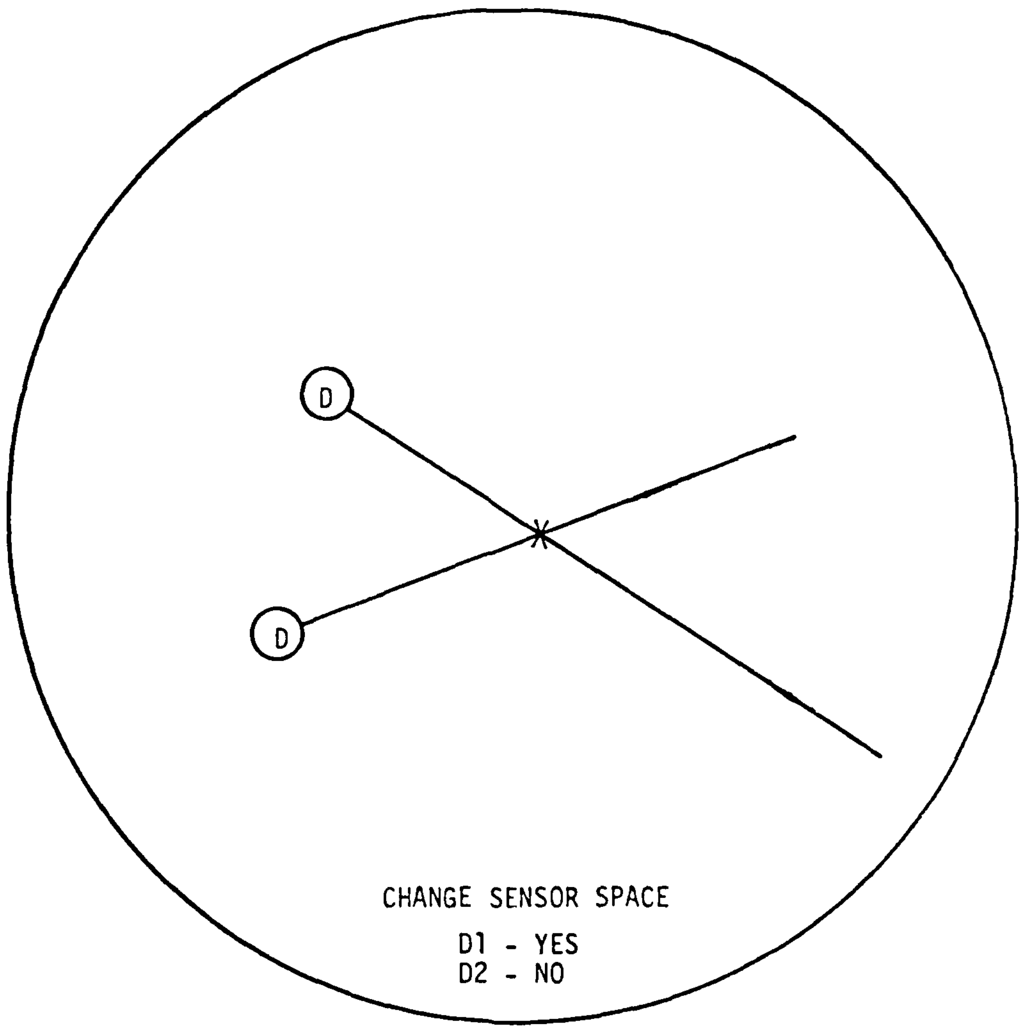


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FIGURE 3-2. SENSOR SPACING TO BE CHANGED?

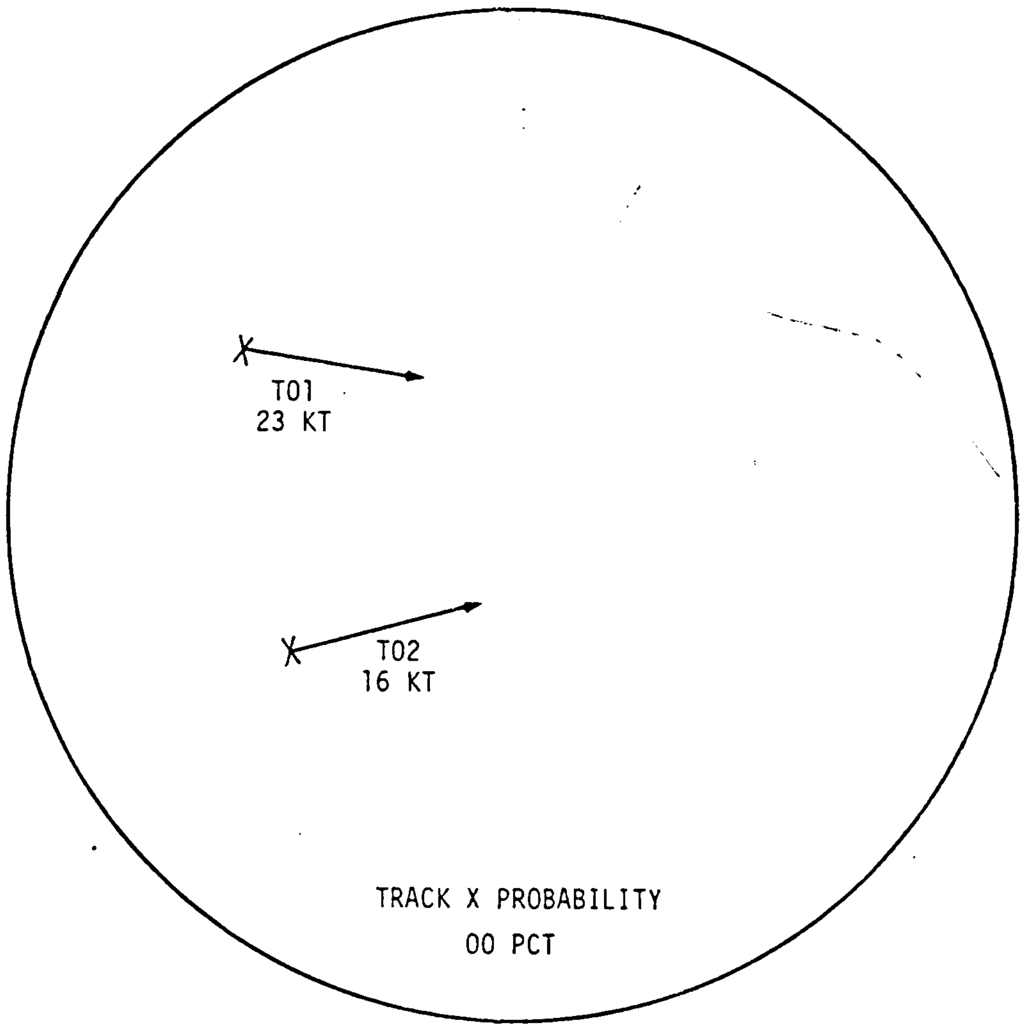

FIGURE 3-3. TACCO WEIGHT ENTRY

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The probabilities for all tracks must sum to 100 for consistency. If they do not, the values are normalized.

3.4 Time to Drop

Because of the current tactical location and orientation of the aircraft (e.g. entering a standard turn), the TACCO may wish to lengthen or shorten the time until the sensors are dropped. The pattern must be completely dropped before the submarine enters its detection range and thus, there is a decision to be made about the estimated time-to-drop based on the current estimated submarine location. The aiding system requests an entry from the TACCO indicating the number of minutes until pattern drop. This information is required to calculate the optimal location for pattern placement.

3.5 Recommendations

Figure 3-4 shows the type of recommendations given by ADA. On the lower part of the display screen are the three best pattern recommendations for sonobuoy deployment. The abbreviations are:

BAR Barrier
WED Wedge
ENT Entrapment
TRI Tri-tac

The single digit immediately following the pattern designation is the recommended number of passive sonobuoys to be used. Figure 3-4 shows a barrier of 8 passive sonobuoys as the best choice; a wedge of 7 passive sonobuoys is the second choice, and a barrier of 5 passive sonobuoys places third.

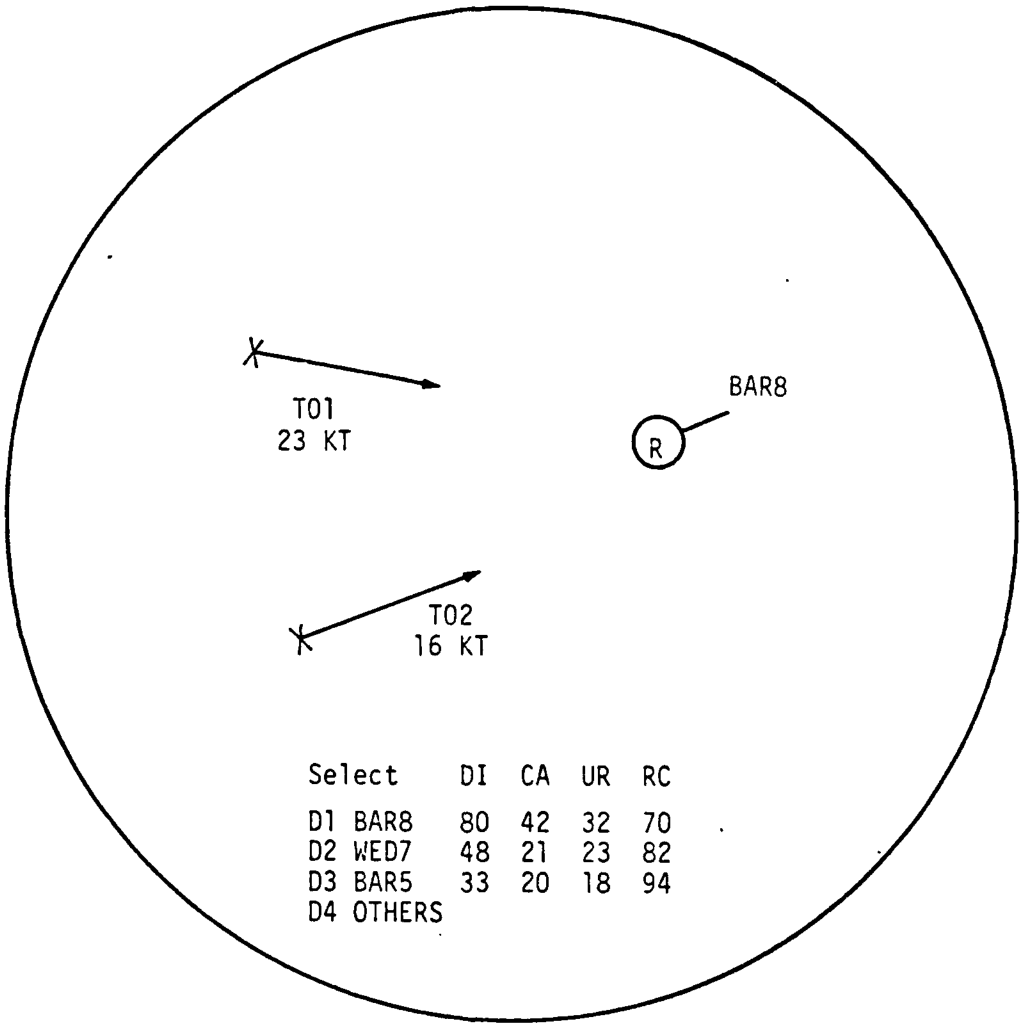

FIGURE 3-4. SENSOR PLACEMENT RECOMMENDATIONS

On the display screen above the pattern recommendations is the optimal location of the best pattern (BAR8 in this example). This is shown by the letter "R" surrounded by a circle. The location is the "anchor" point for the particular pattern (see Figure 3-4). For example, for the entrapment, the anchor point is the center of the circle of sonobuoys. In the wedge, the anchor point is the apex of the wedge angle. Tri-tac has its anchor at the leading buoy and the barrier has an anchor at the center of the barrier line. In addition to the anchor point, a directional orientation line is provided for reference.

After receiving the three best pattern recommendations the TACCO must either choose one of them or reject them all. This is accomplished by using the decision buttons D1 to D4. Each recommended pattern is associated with one decision button (see Figure 3-4), D1 to D3. Button D4 is reserved for "others" which means a rejection of the three recommended patterns.

In order to aid the TACCO in making a choice, pattern characteristic information is provided along with each recommended pattern. This information is in the form of four relative values called "attributes". The four attributes are:

(1) Detector Index (DI)
(2) Coverage Area (CA)
(3) Uncertainty Reduction (UR)
(4) Resource Conservation (RC)

Each attribute is measured on a scale from 0 to 100 and is a primary component of the adaptive algorithm. The TACCO must understand the meaning of each of these attributes before he can use the decision aid effectively (see Section 2.3.3).

3.6 Recommendation Rejection

If the TACCO closes one of the buttons D1 to D3, he is indicating his preference for a recommended pattern. Because of the nature of the utility training algorithm, no adjustments will be made if D1 is chosen, and slight adjustments will be made if D2 or D3 is chosen.

If D4 is chosen, it is an indication that the TACCO is unhappy with all of the three recommended patterns and wishes to choose his own. At this time, an aid to choice appears on the lower part of the screen (Figure 3-5). The four decision buttons are now used to select one of the four possible pattern shapes. After each pattern name is a list of the possible number of sonobuoys for reference. After the pattern shape is selected, the TACCO must enter the desired number of sonobuoys on the keyboard. At this time, the training algorithm adjusts the utilities based on the TACCO's actual pattern choice. In some instances, it may happen that the TACCO prefers to drop a pattern which is totally outside the scope of the decision aid (i.e. a single sensor or an extension to an existing pattern). If this is the case, the TACCO simply cancels the aiding program before it is completed, and no alteration of utilities is performed.

3.7 Environmental States

The adaptive model is linear, combining additively the contributions of the different parameters considered. The influence of variations in weather conditions as well as differing submarine type and behavior is important in the evaluation of the sensor patterns, but this influence is not linear. It crops up as influences in the submarine model, sonobuoy sensitivity range, error rate, etc. These variations are accounted for by defining "states of the environment" which are combinations of state variables. After questioning experienced TACCOs,

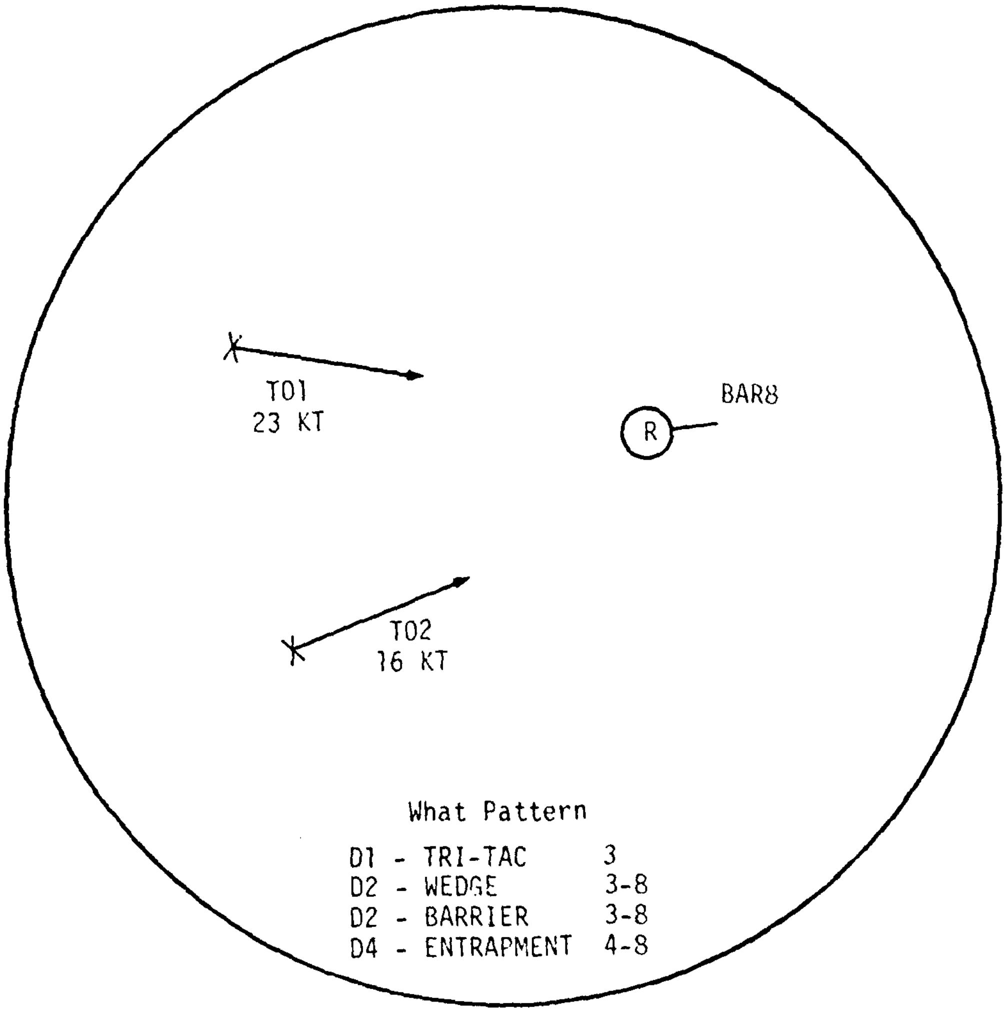

FIGURE 3-5. SENSOR PATTERNS IN DECISION AIDING SPACE

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the number and range of the state variables was narrowed down to the following:

(1)	Sea condition:	a. rough
		b. calm
(2)	Weather condition:	a. stormy
		b. clear
(3)	Submarine type:	a. diesel
		b. nuclear
(4)	Submarine maneuvers:	a. en route
		b. evasive

Each combination of environmental variable values defines a different state of the environment and a different set of parameters is associated with them. The four state variables with two values each produces sixteen possible "states of the world". These parameters are used in calculating the different probabilities in the model. Furthermore, a separate set of utilities is associated with each state of the environment and each such set must be trained separately. Although this requires a longer training period, convergence speed is gained on each set. When the state of the environment changes, the TACCO can indicate such a change and the system will switch to the appropriate set of parameters (pretrained) and can immediately aid the TACCO's decisions in the new situation. Without this provision, the system would have to go through a phase of retraining before it could predict correctly the TACCO's choices for each change in environmental conditions.

The environmental states procedure has been implemented in the model but has not, as yet, been tested.

3.8 System Implementation

This section describes the software structure for the implementation of the decision aiding system. The system was implemented on the P-3C training facility at Moffett Field, San Jose, California, and integrated into the P-3C simulation system at NADC. The vehicle for implementation was the Laboratory Functional Prototype System (LFPS): a self-contained subset of the entire P-3C system developed at NADC. The LFPS was ideal for integrating the adaptive aiding system since it contained a submarine generation package as well as simulated sensor contacts which appeared in the same way as real contacts. Thus, the LFPS was designed to be used by TACCOs while the P-3C aircraft was on the ground.

The display format and switch selection on the TACCO control console are each designed to resemble as closely as possible the standard format used in the current TACCO station. Due to the mathematical calculations in the decision aiding program, the ADA program is segmented into several sections, and only one section is allowed to execute during any updating period. Because of this segmentation, interruptions of the normal operation of the existing P-3C procedures are not apparent to the TACCO.

The adaptive decision aiding program is divided into six components: (1) The Real World Generator, (2) The Adaptive Decision Aiding Model, (3) The Supervisor Program, (4) The Interrupt Handler, (5) The Display Program, and (6) The Accessory Routines. The TACCO interacts with the supervisor program, which monitors the TACCO hardware interface and schedules the operation of all sub-programs. The function of the adaptive decision aiding component is to model the TACCO and the environment, and to aid the TACCO for decision making on how and where to deploy sensors.

The decision aiding system includes the following programs and subroutines.

(1) Real World Generation
   (a) Submarine Model
   (b) Weather Model

(2) Adaptive Decision Aiding Model
   (a) Attribute Generation
   (b) Sensor Pattern Recommendation System
   (c) Utility Adjustment System

(3) Supervisor Program
   (a) Master Systems Scheduler
   (b) Message Data Routine
   (c) I/O Dispatcher

(4) Interrupt Handler
   (a) Interrupt Acknowledgement Routine
   (b) Program Segmentation

(5) Display Program
   (a) Cue Display
   (b) Sensor Pattern Recommendation Display
   (c) Resultant Track Generation

(6) Accessory Routines
   (a) System Initialization
   (b) Automatic Training Technique

The above programs are illustrated in the following paragraphs:

3.8.1 Real World Generation

Submarine Model. The movement of the submarine is modeled in such a way that its speed and heading are updated every five minutes. The speed, ranging from 9 knots to 19 knots, and the heading, ranging from 0 to 156 degrees, are preset in a look-up table, and the real-time counter initiates the updating action. The speed and heading can be modified while the system is running through the on-line debugging routine which is built into the systems.

Weather Model. As the weather condition changes, the weather model selects the appropriate utility vector for the multi-attribute utility model and utility adjustment.

3.8.2 Adaptive Decision Aiding Model

Attribute Generator. This subsystem generates four attributes for each sonobuoy pattern in the decision aiding space. With the proper selection of the adjustment constants, the values of all four attributes fall within the range from zero to one hundred. The four attributes are Detection Index, Uncertainty Reduction, Coverage Area, and Resource Conservation.

Sonobuoy Pattern Recommendation System. This subsystem represents the mechanization of the TACCO behavior model. It computes the expected Multi-Attribute Utility (MAU) for each sonobuoy pattern and selects the pattern with the maximum MAU. This selection is considered the "best" choice in the recommendation list.

Utility Adjustment System. This subsystem trains the utilities whenever the recommended pattern is different from the pattern which is actually chosen by the TACCO. The basic idea of training is to punish the recommendation and to reward the actual choice.

3.8.3 Supervisor Program

Master System Scheduler. This is the supervisory program for the decision aiding system and the TACCO system interface. It can be used by the TACCO to make minor changes in the sequence of events in the decision aiding process. Its main function is to control the calling sequence of the other programs. Figure 3-6 shows a flow chart of this program.

Message Data Routine. Messages to the TACCO are moved from the addresses reserved for messages according to the design of the display image on the multi-purpose data display to the display buffer for later display.

I/O Dispatcher. Communication from the TACCO and messages to the TACCO are handled in two ways. The cue display is performed by calling the cue display routine with the appropriate value stored in the Q-register to indicate whether it is a decision cue or a non-decision cue. The graphic display is performed by calling the re-scale and display routine with display buffer filled with the code of symbols.

3.8.4 Interrupt Handler

Interrupt Acknowledgement Routine. An external interrupt is generated when the decision aiding switch is depressed. The interrupt acknowledgement routine sets the task-active flag in the periodic task table, and the active flag is then sensed for activation of the master system scheduler when the EXEX operating system makes the periodic search. Meanwhile, the task period time is stored in the periodic task table for triggering of the periodic execution of the master system scheduler routine. Similarly, when the decision aiding is terminated, the task period time is replaced by the maximum time in order to prevent the decision aiding routine from getting attention.

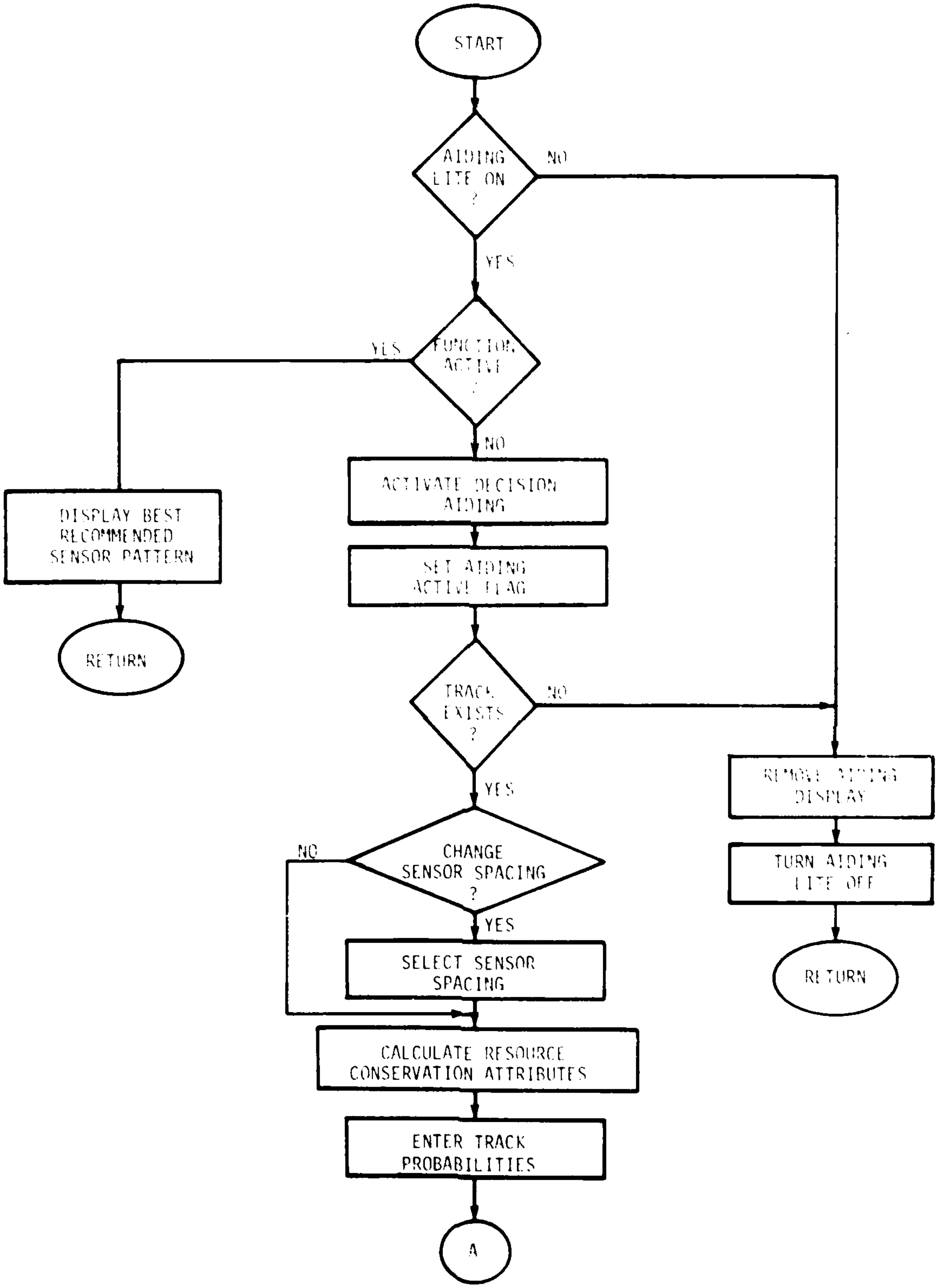

FIGURE 3-6. SUPERVISOR PROGRAM

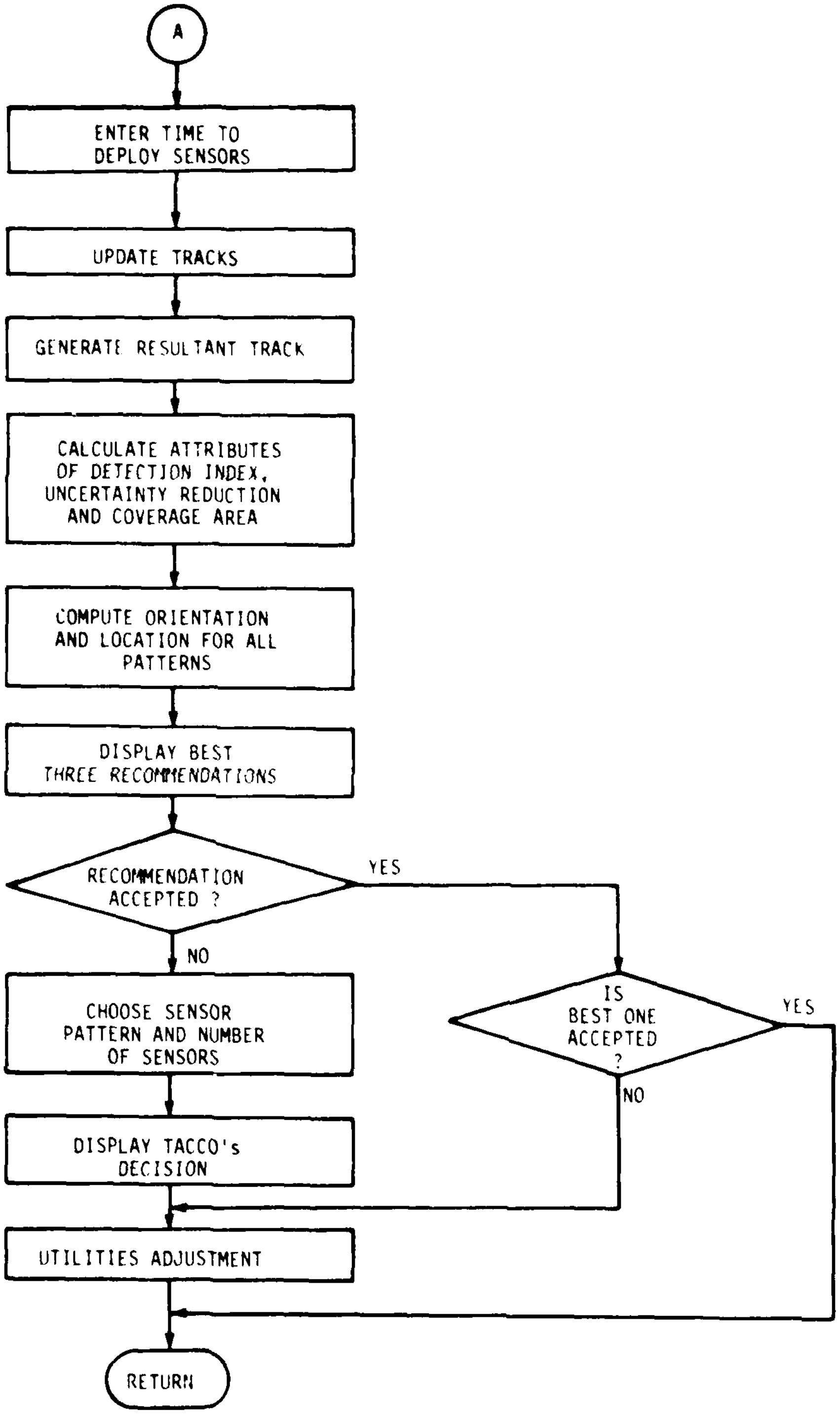

FIGURE 3-6. SUPERVISOR PROGRAM (CONTINUED)

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Program Segmentation. Due to the time constraint of real-time operation, the decision aiding program is segmented into several sections. The segmentation routine directs the control to execute only one section when the decision aiding program gets system attention each time. This will allow all other routines to perform their functions normally when they require services.

3.8.5 Display Program

Cue Display. The cue display data have been coded into the cue tables labeled by the cue sequence. When the cue display is initiated, the address of the labeled table is loaded into A-register, and the Q-register indicates what type of cue to be displayed. One of the decision keys needs to be depressed in order to complete a cue action if it is a decision cue.

Sensor Pattern Recommendation Display. The message for the sensor pattern recommendation is constructed in this routine and stored in a temporary display table. Those data are later retrieved and displayed on the screen by the periodic display routine.

Resultant Track Generator. The displayed data are calculated and formed into a specified format based upon the predicted resultant track. The resultant track is generated with respect to all the existing tracks; the weight of each track and the time to deploy sensor pattern contributes heavily in this calculation.

3.8.6 Accessory Routines

System Initialization. The LFPS system initialization routine calls the accessory routines routine to initialize all the variables and constants used in the decision aiding program.

Automatic Learning Routine. If the automatic learning technique is activated, the decision aiding system makes its own decision based upon the expert's utilities without any TACCO interference for decision making. This learning routine will make decisions in such a way that the system utilities will eventually adapt to the present experts utilities.

4. EMPIRICAL EVALUATION

4.1 Overview

A preliminary evaluation study was performed in order to test the Adaptive Decision Aiding system operation, verify its computational functions, and measure its acceptance by the TACCOs. The precise objectives of the evaluation were as follows: (1) to evaluate the TACCO display and control, (2) to identify required changes and improvements, (3) to verify system operation in terms of computational functions, adaption, and strategy learning behavior, and (4) to demonstrate the system operation to experienced TACCOs to determine system potential for future tactical ASW operations.

4.2 Functional Tests

4.2.1 Utility Convergence. Convergence is the key element of adaptive decision aiding. If a model converges, it indicates that (1) the decision strategy of a TACCO can be observed and learned by the model in ASW Task environment, and (2) the decision model can be reliably used for decision recommendation feedback. It is thus a key functional test in system evaluation to determine whether the model utilities are converging and to examine the rate of the convergence (that is, the number of trials required for convergence)(Freedy, Davis, Steeb, Samet, and Gardiner, 1976). Convergence can be defined as the level which is approached by the model utilities while observing a given, consistent decision strategy. The MAU model parameters are continuously being adjusted as shown in Figure 4-1 until the model's recommended decisions agree with the actual decisions that are being used to train the model.

This test reported here, involved the ADA monitoring the performance of repeated sensor allocation decisions where a predetermined,

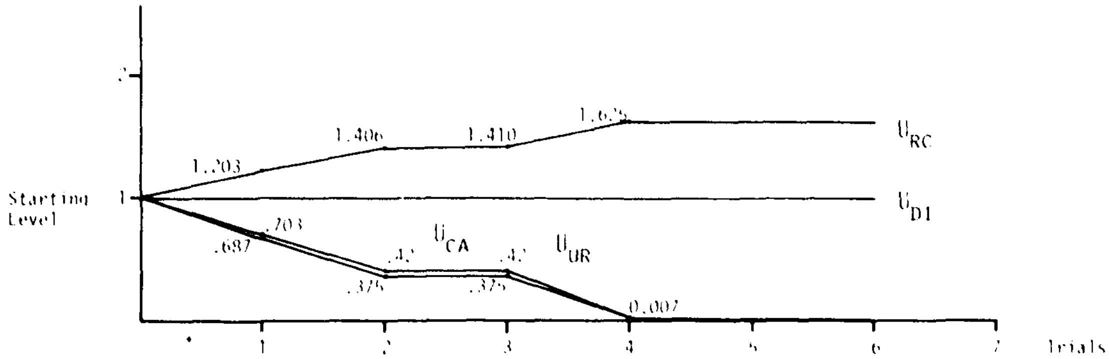

FIGURE 4-1. SYSTEM ADAPTIVE UTILITY LEARNING CURVE

stable decision strategy was employed. Figure 4-1 illustrates the convergence curves of the model. As shown, the four utilities U_{RC}, U_{DI}, U_{CA}, and U_{UR} converged after four trials. The model therefore is said to be convergent after that period since no more changes in utilities occur. This is an indication that the model has acquired the decision strategy used by the operator. Under the experimental strategy, high value was placed on Resource Conservation (RC), and low value was placed on Uncertainty Reduction (UR). Comparing this curve to earlier results in adaptive decision models, it is apparent that the curve reflects good adaptability of the model and the proper range in the learning parameters (Steeb, Chen, and Freedy, 1977).

4.2.2 Convergence Accuracy. Convergence accuracy indicates how well a model can learn specific utility ratios from a given decision strategy and illustrates the accuracy level to which the model can be adapted.

Figure 4-2 shows the learning utility strategy curve in the decision model. The broken line shows the utility ratio U_{RC}/U_{DI} that is used in "training" the model, while the solid line illustrates the learned strategy U_{RC}'/U_{DI}' as shown. The utility ratio converged to within 15% of the training strategy indicating adequate model accuracy. This example indicates the model adaptability to a given strategy.

4.2.3 Dynamic Behavior. Dynamic behavior measures model capability to adapt to new decision strategies in the event a TACCO changes strategies. Dynamic behavior of the ADA model was tested by employing a number of different tactical strategies and alternating between them while tracking a submarine on the LFPS. It has been shown through the data that ADA will recognize and adapt to a strategy change within two trials on the average. These results indicate adequate adaptiveness of the model. However, it should be emphasized that the adaptability of the model can be fine-tuned by changing the increments by which utilities are being modified. The

U_{RC} - Resource Conservation Utility

U_{DI} - Detection Index Utility

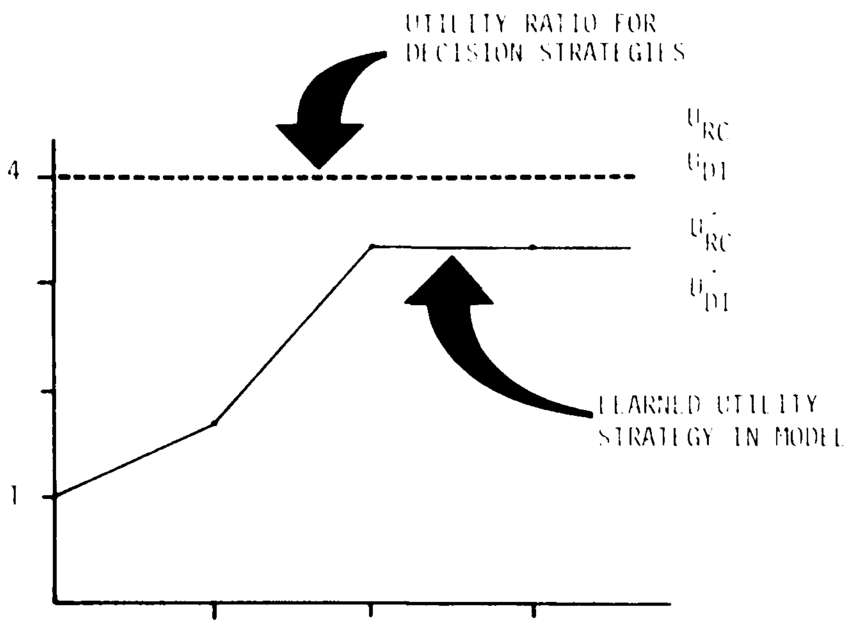

FIGURE 4-2. SPECIFIC STRATEGY LEARNING EXAMPLE

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results achieved here merely indicate that the model adaptability and computational functions for changing strategies is operational and can achieve satisfactory dynamic behavior for operational utilization.

4.2.4 Response Time. System response time indicates the computational time that is required to generate a decision aiding recommendation following the TACCO's probability entry and his request for decision aiding. This time covers all the computational functions which are required to adjust model parameters and compute and display the optimal sonobuoy patterns. The system response time varies with the number of tracks that are being processed simultaneously by the adaptive decision aid. Figure 4-3 illustrates the system response time as a function of a number of tracks. The system response time ranges from 2.2 seconds for one track, to four seconds for four tracks. This response time is adequate and is within the range of an acceptable man-computer interaction response time (Miller, et al, 1967).

4.3 Subjective Assessment

To evaluate the acceptability of the adaptive decision aid, a questionnaire was developed to obtain attitudinal responses from a selected group of individuals. The collection of such attitudinal data provides valuable information regarding reactions, feelings, and preferences toward the aiding system. Since attitudes are an important determinant of behavior, questionnaire responses from a representative group of potential users allow a reliable estimate of what the reactions might be to the aid in actual field use. These reactions also may be used to anticipate and resolve potential problems during development to insure their avoidance in future applications. The questionnaire was a 12-item open-ended questionnaire, a format usually preferred for obtaining subjective data from a small group. The decision aid was

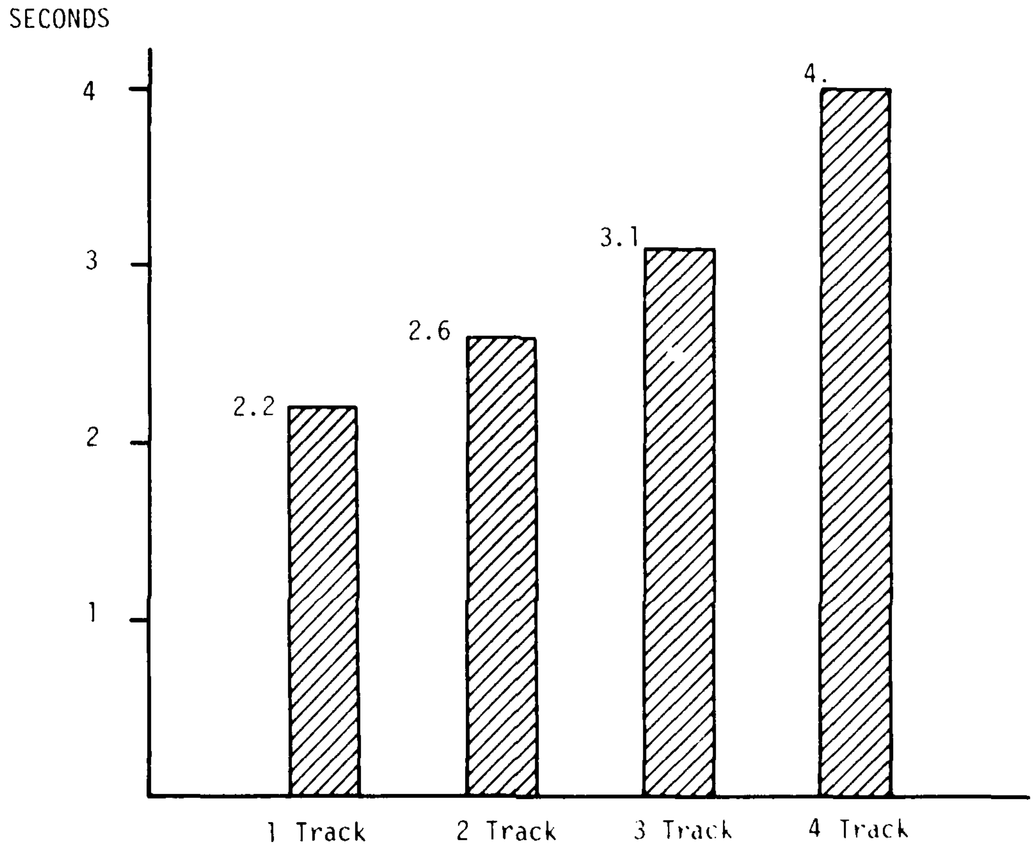

FIGURE 4-3. COMPUTATIONAL TIME OF DECISION RECOMMENDATIONS

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demonstrated to five TACCO instructors, to assess their initial reactions to the decision aid. The results of these questionnaires appear in full in Appendix A.

4.3.1 Operator Acceptance. Overall, the reaction to the aid was quite positive. Four of the five subjects indicated they would like to see such an aid installed on the P-3C aircraft, while one subject preferred to defer his judgment until a more formal test and evaluation of the system was carried out. Two subjects showed some concern about the amount of core available. All subjects felt that the aid made pattern selection more effective. Three out of five thought it helped in overall job effectiveness, one thought it helped only in certain situations, and one deferred his initial judgment until he had more experience with the aid during actual flight conditions. In general, all subjects thought the aid would make it easier for them to carry out their tasks.

The subjects' responses to speed of decision with the aid were mixed. Four of the subjects thought both the organization of the display and the procedures for using the aid were acceptable, while one subject remained neutral. When asked what advantages and/or disadvantages the aid had when compared to manual methods, all subjects listed only advantages. In summary, these included (1) standardizing procedures with a rational basis, (2) aiding the decision processes, and (3) time savings.

4.3.2 Data Entry. In terms of data entry procedures for situation estimates, four of the subjects felt the procedure for entering probability estimates was acceptable, and one thought a direct switch entry of probability ranges would save time. The one subject who wanted the probability entry procedure changed thought the procedure could have been integrated with the probability control matrix function already available at the TACCO station. This suggestion should be investigated as it may offer the potential for higher overall system effectiveness.

4.3.3 Training Impact. The general opinion of the subjects was that the aid impacted minimally on training requirements. The time estimates ranged from 15 minutes to 8 hours. Nevertheless, the reactions of the subjects to the ease of understanding the attributes suggest that some improvements could be made in this area. Responses from four of the subjects suggests that choosing attributes that are already used by the TACCOs and thus standardized, would improve the ease of understanding and the effectiveness of the aid.

4.3.4 System Changes. When asked what improvements/changes they would suggest for the aid, three of the subjects suggested essentially the same thing, expressed in different ways. They would like to have a display aid that would graphically show the buoy patterns. In addition, two of the subjects suggested integration with existing software that produces flight instructions for the pilot.

5. CONCLUSION

The installation and preliminary testing of the adaptive decision aid in the P-3C aircraft simulators has demonstrated its application to TACCO decision making tasks. Moreover, implementation feasibility within the current computational and task constraints of the system has been demonstrated. With respect to general application, the P-3C development has shown that adaptive decision methodology fits the task domain of general tactical decision making. It also has demonstrated that such a model can effectively describe the ASW tactical environment and can "capture" pattern selection strategies. The critical factor which has been shown is the compatibility of ADA with existing tactical environments. This operational decision aid has been incorporated into the TACCO structure with no detectable interference to the TACCO or with team operations. With respect to implementation feasibility, it has been shown that feasible hardware/software interfaces can be developed and that the computational functions of adaptive decision aids can be interfaced efficiently into the existing software and hardware computer systems. In particular, the information display and required data input can be accomplished using already existing TACCO multi-purpose data displays and control panels. With respect to actual tactical operations, it has been demonstrated that given an operational computer, ADA is able to provide satisfactory response time to operator requests for aiding. This prototype system thus provides the first step of a transition from basic research to operational systems technology. The current system can already be used as a practical demonstration and evaluation tool of decision aiding in airborne operations and could easily be expanded to other types of aircraft. Also, implementation of the aid appears feasible on any high-performance aircraft or shipboard operations which involve large amounts of data and repetitive action selection under stress (such as radar intercept operations, AAW, and so on). Since the aid is operational in a simulated command and control test facility, one of the

main questions that can now be studied is the procedure and criteria for evaluating operational crew acceptance of decision aids and evaluating the training requirements necessary to introduce such systems into tactical fleet operations.

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APPENDIX A

TACCO EVALUATION
QUESTIONNAIRE

PARTICIPANTS:

FASOTRAGRUPAC TACCO INSTRUCTORS

(Lt. JG through Lt. Cdr.)

QUESTION

2. *Do you feel that the computerized aid for sensor pattern selection would:*

   a. *Help you do the job more effectively overall?*

      TACCO A: Yes

      TACCO B: Yes

      TACCO C: Yes

      TACCO D: I think I could only make this judgment in a real aircraft against a real submarine.

      TACCO E: In certain situations.

   b. *Help make it easier for you?*

      TACCO A: Yes, but only in certain flight modes (localization) Pass Trk

      TACCO B: Yes

      TACCO C: Yes

      TACCO D: Probably

      TACCO E: When there is sufficient time to react.

   c. *Help make pattern selection more effective?*

      TACCO A: Yes

      TACCO B: Yes

      TACCO C: Yes

      TACCO D: Yes

      TACCO E: Yes

   d. *Help make selection decisions faster?*

      TACCO A: No

      TACCO B: This depends on experience level of TACCO. If TACCO is very experienced, he may consider it a nuisance and not use it. If TACCO is inexperienced he will rely on it and it will make selection decisions faster.

      TACCO C: Yes

      TACCO D: Probably. If not, it should allow for a better decision in the same time (included in this is blindly accepting the D-1 recommendation when no time is available).

      TACCO E: Not necessarily. I would need to evaluate the entire program in an aircraft under actual situations to formulate a better feel for its capabilities.

QUESTION

2. *Is the procedure for entering probability estimates acceptable in terms of time and effort?*

TACCO A: Yes, however probability estimates are just that: estimates from TACCO. It seems that the entire process is based on this one input.

TACCO B: Possibly use of decision switches would save TACCO some time.

Example

Median			
15%	10% - 25%	D1	use median in each group for your calculations
40%	30% - 50%	D2	
70%	60% - 75%	D3	
90%	80% - 100%	D4	

TACCO is never 100% sure. This would save TACCO several key depressions.

TACCO C: Yes

TACCO D: Yes

TACCO E: Not really. I think that the procedure could possibly be accomplished through some of the functions already available such as probability contour matrix readout button.

QUESTION

3. *How easy is it to understand the attributes that are to be used in comparing recommendations?*

TACCO A: Very

TACCO B: Could be simplified for easier understanding

TACCO C: Somewhat confusing at first; but had little time to look the information over prior to the test. Once explained, they are easily understood.

TACCO D: I need more help with this.

TACCO E: Not very difficult when related to our terminology.

QUESTION

4. *How much training would be necessary in order to use this aid during an actual mission?*

TACCO A: Very little, 15 minutes of personal instruction

TACCO B: Minimal

TACCO C: Very little. A one-hour lecture would accomplish it.

TACCO D: 1/2 day lecture to explain the aid and define all attributes followed by two 2-hour trainer (WST) periods to put it into practice. I am assuming that one is starting with a qualified TACCO.

TACCO E: Hard to say -- at least a couple trainer periods and stress the use of it throughout his training.

QUESTION

5. *Is the procedure for accepting and rejecting recommendations acceptable in terms of time and effort?*

TACCO A: Yes

TACCO B: Not familiar enough

TACCO C: Yes

TACCO D: Yes

TACCO E: Seems adequate. I believe the total number of recommendations could be limited to max. 3 or 4.

QUESTION

6. *Can you suggest more useful ways to organize the display of recommendations?*

TACCO A: No, already in standard format of information currently displayed.

TACCO B: Notfamiliar enough

TACCO C: No

TACCO D: No

TACCO E: Display is alright.

QUESTION

7. *What advantages/disadvantages do you see for this aid compared to manual methods?*

TACCO A: Aids TACCO in positioning patterns and helps in sonobuoy management.

TACCO B: Would standardize procedures (see note Question 1 d)

TACCO C: Helps a great deal in the decision process at the T/C Station.

TACCO D: 1) Time savings; 2) Having the ability to select a pattern based on reasonable accurate attribute values; 3) If time becomes super-critical, just select the D-1 recommendation and go. This could bail the TACCO out of a time crunch.

TACCO E: The computer can be programmed to stress certain attributes, coming up with the most logical patterns. Could be very useful under certain limiting operations.

QUESTION

8. *What improvements/changes would you suggest for the aid?*

TACCO A: Show buoy positions for selected patterns.

TACCO B: Not familiar enough.

TACCO C: None. I liked it.

TACCO D: When a pattern selection is made from those options offered by the aid, the expendable fly-to-points should be displayed at the recommended positions. Once the TACCO sees this, he could respond to the one D-1 ACCEPT D-2 REJECT D-3 MODIFY and be on his way to drop the sonobuoys. Additionally, buoy selection (type, life, depth) must be part of the sequence.

TACCO E: Limit the number of patterns and the amount of steps to come up with a pattern. Also program the computer to go into building the pattern after the TACCO has made his selection.

QUESTION

9. *Would you like to see such an aid, with necessary improvements, installed on the P-3 aircraft?*

TACCO A: Yes, if I don't lose any computer space (function already available)

TACCO B: Yes, if core would allow.

TACCO C: Yes, very much.

TACCO D: Yes.

TACCO E: Would need to evaluate it more - under controlled situations in the trainer.

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This report describes the results of a research and development program directed toward the application and demonstration of Adaptive Decision Aiding (ADA) in anti-submarine warfare (ASW).

The aim of the adaptive decision aid is to enhance the performance of the Tactical Coordination Officer (TACCO) aboard the Navy P-3 aircraft the sonobuoy pattern selection phase of airborne ASW tactics through interactive

decision aiding software. The software ~~utilized~~ used adaptive techniques to "capture" a TACCO's decision making strategies and then recommends future actions on the basis of objective criteria and learned objective values.

The empirical evaluation results have shown that (1) the methodology of adaptive decision aiding can effectively be transferred to the task domain of tactical decisions; (2) it is feasible to implement and integrate decision aids into existing TACCO decision task structure and P-3 operational computer hardware; and (3) the ADA receives good acceptance from TACCO instructors. In addition, the research program has also produced a useful demonstration and evaluation tool for further development and evaluation as this system transitions to operational use.

This report describes the technical details of the ADA system and its integration into an existing P-3C simulator at the Naval Air Development Center (NADC), and presents a system overview demonstration and preliminary experimental evaluation. The report reviews the theoretical structure of the adaptive decision aiding model and presents a brief description in decision analysis in terms of the TACCO tracking decision tasks. A description of the P-3C ADA software is given, together with technical details regarding system integration into the CP-901 P-3C computer. Results of empirical evaluation and demonstration that were performed are described.