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ADAPTIVE ESTIMATION OF INFORMATION VALUES IN CONTINUOUS DECISION MAKING AND CONTROL OF ADVANCED AIRCRAFT

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20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

This report describes research and development centered on evaluation of information needs in advanced aircraft operations. The selection of information for display is a recurrent, subjective decision involving many factors -- aircraft state, environmental conditions, operator capabilities, and acquisition costs, among others. An adaptive computer model has been developed which incorporates these factors into a multi-attribute decision model. The program is designed to capture the operator's information seeking policy using a over training algorithm based on pattern recognition techniques. The individual policy is then used for information system evaluation and for automated information management.

Experimental tests of the adaptive modeling and information management approaches were made using a task simulation resembling multiple intercept operations in advanced aircraft. Individual subjects (12 in study) navigated a simulated aircraft through a hazardous, changing environment. In doing so, the operators selected from five information sources of varying content, cost, delay and detectability. The information was then used to take one of a number of control actions. Information management; using either adaptive estimation or off-line direct policy elicitation, was found to result in improved task performance over manual selection, particularly in high speed stress conditions. The adaptive estimation technique was found to be superior to direct policy elicitation, both for automated information management and as a basis for information source evaluation. Possible applications of the techniques are also discussed.

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1. INTRODUCTION

1.1 Summary

This report covers the second year of a three-year program of research and development directed toward evaluation of information needs in decision making and control of advanced aircraft. Its purpose is to establish new techniques for the selection of essential information in operational systems. These techniques center on the adaptive modeling of individual decision behavior to derive the immediate value of information. The program will result in aids for the real time management of communications. Specific objectives of the three year program include the following:

(1) Establish a repertoire of techniques to model the information needed for operation of tactical airborne systems.

(2) Provide model-based computer programs capable of ascertaining the potential usefulness of alternative information sources, transmission systems, and information displays.

(3) Develop and experimentally validate a supervisory program for management of communications in simulated tactical airborne systems.

(4) Produce guidelines for field application of the information analysis and management programs in a variety of complex systems.

The initial year's work established techniques for modeling the information seeking decisions necessary for continuous decision making and control of remotely piloted vehicles. The work also experimentally

demonstrated the usefulness of adaptive techniques for prediction and analysis of information seeking behavior. The work reported here builds on these findings by investigating the usefulness of the adaptive decision model for automating the presentation of information and for evaluating the effectiveness of information display configurations.

1.2 The Problem

Command and control of modern military systems involves selection among increasing large amounts of information. Computerized systems typically make available copious amounts of information concerning remaining resources, environmental state, potential computer aiding, and predicted circumstances and actions. The costs of communications and the limited processing capabilities of the human operator make it necessary to optimize the information selected, transmitted and presented.

The central problem in performing an analysis of information needs is the structuring of the decisions. Choices must be modeled regarding variables such as the mix of information sensing, processing, encoding, transmitting, and display. Throughout this process, a balance must be maintained between maximizing operator awareness of system operation and minimizing communications costs and operator load.

Some initial efforts have been made toward analyzing and automating the communications management functions. Information and control allocation techniques have been proposed using criteria based on queing models (Rouse, 1975; Engstrom and Rouse, 1976), optimal control models (Sheridan, 1976; Rouse and Gopher, 1977), and multi-attribute decision models (Steeb and Freedy, 1976). This program represents an effort to develop, integrate and implement the more promising of these techniques.

1.3 Technical Approach

In brief, the command and control task can be represented as a multi-stage decision task of information acquisition and action selection. The effectiveness of the action decisions are dependent on the appropriateness and timeliness of the information acquired. The choices of what information to transmit thus must reflect the task circumstances, the operator's and automatic system's capabilities, and the communication channel characteristics. These decisions can be expressed analytically using a multi-dimensional set of utilities tied to the potential consequences of the actions. The weights of the various dimensions reflect the importances placed by the individual decision maker on each factor.

A program was developed along these lines, containing both objective probability estimation algorithms and subjective behavioral models. The probability estimation algorithms calculate the likelihood of occurrence of consequences. Such algorithms depend on frequency determinations and optimal Bayesian calculations. The subjective models use these determinations as inputs and are adaptive multi-attribute forms tied to prediction of behavior. The models demonstrate potential for a number of types of aiding. Among the uses planned are evaluation and specification of communication configurations, individualized training in information acquisition, and automated communications management.

Testing of the models was accomplished by determining the aiding and analysis capabilities provided in a advanced aircraft task simulation. The task simulation incorporates many of the functions involved in multiple intercept operations and has extensive performance analysis capabilities.

1.4 Current Objectives

The focus of this phase of the research and development program is to extend the application of the adaptive decision model to include information evaluation and management functions in an advanced aircraft context. This builds on the findings of the initial year's work in which the adaptive program was found to be a useful model for analyzing and predicting information seeking behavior. The specific objectives of this second-year program include:

(1) Extend the review of the engineering and psychological literature to include airborne information selection and presentation.

(2) Modify the multi-attribute decision model developed for RPV supervision to one capable of dealing with information selection in advanced aircraft. Additional factors for time stress and an expanded action set are to be included.

(3) Develop a task simulation resembling multiple intercept operations in advanced aircraft. Install computer programs for parameter estimation, information value assessment, and communications management.

(4) Conduct an experimental study of the effectiveness of the multi-attribute model for information system evaluation and for automated information management. Direct operator control of information is used as a baseline for comparison.

1.5 Report Organization

The organization of this report is as follows: Chapter 2 reviews selected background concepts, traces the development of the adaptive models, and describes previous experimental studies performed under this program. Chapter 3 discusses the application of information value modeling to advanced aircraft decision making and control tasks. Chapter 4 describes the experimental plans and procedures for testing the usefulness of the adaptive models. Chapter 5 summarizes the results of the experimental study. Chapter 6 closes with a discussion of the research findings and opportunities for application.

2. INFORMATION VALUE MODELING

2.1 Overview

The selection, aquisition and processing of information are activities that are involved in virtually every aspect of tactical airborne operations. The operator must continuously maintain an awareness of the aircraft state, the environment, the capacity and quality of the communication channels, and the progress toward objectives. This section will explore the more important techniques of modeling these information-related activities.

2.2 Information Seeking Models

2.2.1 Cue Regression. The cue regression approaches, exemplified by Brunswik (1940, 1952), Dawes and Corrigan (1974), and Anderson and Shanteau (1970), are the more descriptive of the two methodologies. In cue regression, a single linear model aggregates a variety of independent factors to predict behavior. Each factor is scaled and weighted according to importance. The influences of the individual factors are then combined additively, multiplicatively, or in some other fashion to arrive at an evaluation of each information choice. The formulation for the simple additive case is:

$$R = \sum_i W_i S_i + C \qquad (2\text{-}1)$$

Where R is an interval scaled performance response, S_i is the stimulus level on dimension i, W_i is the regression weight, and C is an optional scaling constant. The advantages of the cue regression approach are its simplicity and robustness. Virtually any available predictive factors can be used, such as information content, data perishability, channel quality, and operator load. In fact, the ensuing action decision does not even have to be represented. The terminal decision is simply assumed to drive the operator's information seeking behavior. Also, the linear model has been shown to be robust to inaccuracies in modeling, and highly predictive of behavior in a variety of situations (Dawes and Corrigan, 1974; Slovik, Fischhoff, and Lichtenstein, 1977).

2.2.2 Multi-Attribute Utility Models. The multi-attribute utility (MAU) models, pioneered by Raiffa and his colleagues (Raiffa, 1969; Keeney and Raiffa, 1975) and by V. Winterfeldt (1975), tend to legitimize the process begun by the cue regression models. The MAU models make the information seeking process more goal directed, normative and axiomatic. Instead of simply attempting to predict behavior on the basis of a set of independent features, the utility models tie the information decisions directly to the ensuing action decisions. The value of obtaining information is determined by calculating its impact on the expected utility of the subsequent action decision. The information is assumed to change the probability distributions of the consequence sets and, in turn, to revise the expected values of the alternative actions. Nevertheless, the form of the model is again a linear additive rule. The utility of an action is considered to be an aggregate of many possible outcomes, each expressed along a set of attributes:

$$EU\,(a_k) = \sum_{\substack{\text{states}\\ h}} P(z_h) \sum_{\substack{\text{attributes}\\ i}} U_i\,(a_k, z_n) \qquad (2\text{-}2)$$

Where $EU(a_k)$ is the expected utility of action k, $P(z_n)$ is the probability of state z_n occurring, and $U_i(a_k,z_n)$ is the utility function over the i^{th} attribute associated with state h and action k. The formulation is the result of several key simplifying assumptions. The decision maker is assumed to be risk neutral, so that he is indifferent between the expectation across a set of uncertain outcomes and the uncertain outcomes themselves. This allows the probabilities to be entered as simple coefficients. Also, the attributes are assumed to satisfy additive independence, allowing the linear additive form of aggregation. Tests for compliance with these assumptions can be found in V. Winterfeldt (1975) or Keeney and Raiffa (1976).

The impact of a message or item of data is to change the probability distribution of the states z_h. Once the message is received, a maximum utility action $a^*(y)$ can be identified. The expected utility of selecting an information source S then becomes (Emery, 1969):

$$EU(S) = \sum_{\substack{\text{messages} \\ y}} \sum_{\substack{\text{states} \\ z}} P(z_h)\, P(y|z_h)\, u(a^*(y),z_h) \qquad (2\text{-}3)$$

Here $u(a^*(y),z_h)$ is the utility of taking action $a^*(y)$ given that state z_h occurs. The utility function is again multi-attributed, but for simplicity $u(a^*(y),z_h)$ is portrayed as having already been aggregated across the various dimensions.

This type of analysis, championed by such researchers as Emery (1969), Marshak (1971) and Wendt (1969), is suited for highly structured tasks. Not only must the possible states, messages, actions, and outcomes be specifiable, but the prior state probabilities and the conditional probabilities characterizing the information system must be derivable. The sequence of decision stages can be depicted using a decision tree, as shown in Figure 2-1. The tree is folded back by associating with each possible message the maximum expected utility of the subsequent actions. This folding back represents graphically the process of EU maximization. The favored information source S is then identified by comparing the expectations taken over all possible messages.

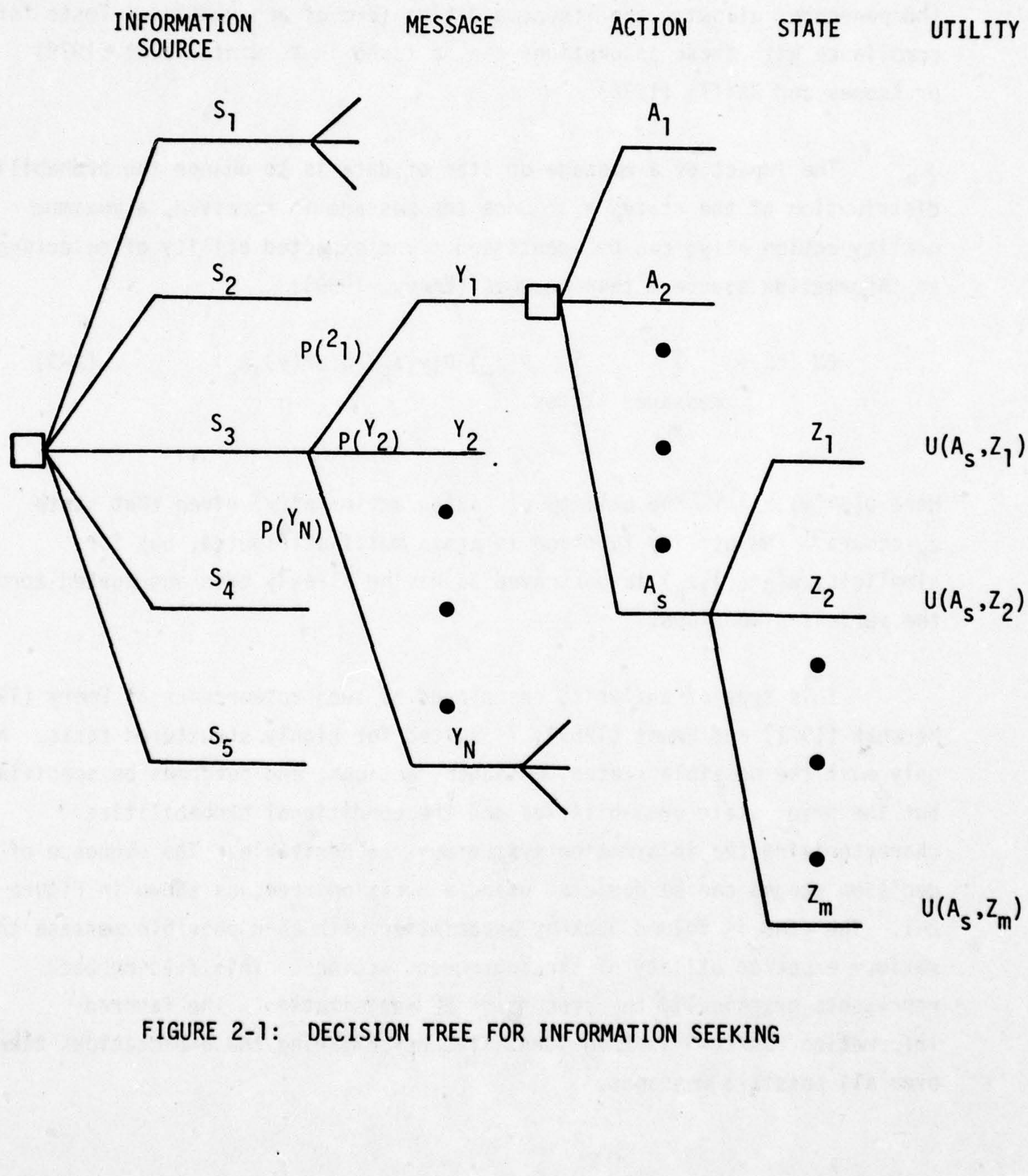

FIGURE 2-1: DECISION TREE FOR INFORMATION SEEKING

Should these requirements be satisfied, diverse aids are possible with the utility model. Alternative configurations for communications can be compared according to their contribution to the attainment of immediate system objectives. The operator's consistency between information seeking and action decisions can be ascertained and corrective feedback given. Also, the automated management of communications can be based on the expected impact on action effectiveness, rather than on the simple mimicry of operator behavior provided by the cue regression approach.

2.2.3 Other Methodologies. A number of other techniques have also been proposed to model information seeking behavior. Among these are information theory models, (Whittemore and Yovits, 1973), optimal control formulations, (Sheridan, 1976; Rouse and Gopher 1977), queing models, (Rouse, 1975; Engstrom and Rouse, 1976), and information intergration techniques (Anderson and Shanteau, 1970). For the most part, these techniques demand rigid problem structuring and continuous variables. More often, the communication decision is incompletely defined and involves choices among discrete rather than continuous alternatives. Thus the discrete operators used in cue regression and multi-attribute utility models - matrices, difference operators, and detailed parameter enumerators - are more appropriate. The interested reader is directed to the previous technical report (Steeb, Chen and Freedy, 1977) for a more detailed examination of these approaches.

2.3 Adaptive Estimation Techniques

2.3.1 Background. The initial year of work on this program resulted in development of a methodology for adaptive estimation of information value parameters. The methodology is based on the use of multi-attribute utility theory to incorporate the various objective and subjective factors that enter into the information decision. The adaptive nature of the program derives from the use of a training algorithm based on pattern recognition techniques to derive certain of the model parameters.

This section traces the structuring of an adaptive information seeking model within a general multi-attribute utility framework: definition of the attribute set, determination of model form, specification of attribute levels and estimation of importance weights. The specific application of this methodology to aiding in advanced aircraft operations will be described in chapter three.

2.3.2 Factor Choice. It was noted in the previous study (Steeb, Chen and Freedy, 1977) that the attribute set should be accessible, monotonic, independent, complete and meaningful. Also, a single set must account for both information acquisition and action selection behavior. Finally, the attribute set must be manageably small in dimension. With these considerations in mind, an initial taxonomy of consequences can be organized around the following five areas:

(1) Communications costs - such as energy, equipment, and attention.
(2) Equipment attrition - fuel expenditures, vehicle damage, etc.
(3) Objectives attainment - area reconnoitered, payload delivered
(4) Dynamic effects - effects on availability of future information and on system capabilities.
(5) Subjective factors - preferences regarding control continuity, operator load.

A useful consequence set might contain a single dimension or attribute from each of these categories.

2.3.3 Attribute Level Determination. The level or quantity of each attribute for a given outcome can be determined in several ways. For example, mappings between predictive features and the attributes can be established by observation and adjustment. Here, data available to the decision program concerning the environmental state, vehicle state, channel characteristics, sensor capabilities, and operator load can be used to predict the attribute levels. Alternatively, the attribute levels may be estimated subjectively or established from performance histories. Use of mappings from predictive features is more attractive than subjective estimates as no load is imposed on the operator, and situation-specific factors may be taken into account. For example, the communication delay may be directly predicted from sensor queue length, sensor response characteristics, and transmission distance. Subjective estimates or pre-established values for the attribute levels would tend to be much less reliable than such in-task calculations.

2.3.4 Attribute Weight Estimation

The policy defining factors in the model, the importance weights k_i, are parameters suitable for either objective or subjective estimation. If the consequences can be defined along objective scales (dollars, ship-equivalents, etc.), then the weights could be derived by analysis and input prior to system operation. Unfortunately, Felson (1975) states that only in a few highly structured situations can such an optimal model be derived. More often, the operator's goal structure, expressed as importance weights, must be elicited or inferred and then incorporated in the model. There are a number of advantages to such subjective estimation, particularly with respect to allocation of function. By incorporating individualized operator weights in the model, the complex evaluation and goal direction functions remain the responsibility of the operator, while the normative aggregation functions are assumed by the computer. Also, operator acceptance of aiding by the model may be increased since his preferences are incorporated in the machine decisions.

The operator's subjective weights may be defined off-line by elicitation or on-line through inference. The off-line methods include direct elicitation of preference, decomposition of complex gambles into hypothetical lotteries, and use of multi-variate methods to analyze binary preference expressions. These techniques are accurate and reliable in many circumstances, but they have a number of disadvantages when applied to operational systems. Typically, these methods require two separate stages -- assessment and application. Assessment requires an interruption of the task and elicitation of responses to hypothetical choices. Problems arise with such procedures since the operator's judgments may not transfer to the actual situation; the decision maker may not be able to accurately verbalize his preference structure (Macrimmon and Taylor, 1972); and the judgments made in multi-dimensional choices are typically responses to non-generalizable extreme values (Keeney and Sicherman, 1975).

Estimation techniques relying on inference from in-task behavior may be more useful. The inference techniques can be based on non-parametric forms of pattern recognition. Here a model of decision behavior is assumed and the parameters of the model are then fitted by observation and adjustment. Briefly, the technique considers the decision maker to respond to the characteristics of the various alternatives as patterns, classifying them according to preference. A linear discriminant function is used to predict the decision maker's choices, and when amiss, is adjusted using error correcting procedures. In this way, no preference ratings or complex hypothetical judgments are required of the operator.

The adaptive nature of the estimation program is shown in Figure 2-2. Expected consequence vectors associated with each information source are input to the model. These consequence vectors are dotted with the weight vector, resulting in evaluations along a single utility scale. The maximum utility choice is determined and compared with the operator's actual choice. If a discrepancy occurs, the weight vector is adjusted according to the following rule:

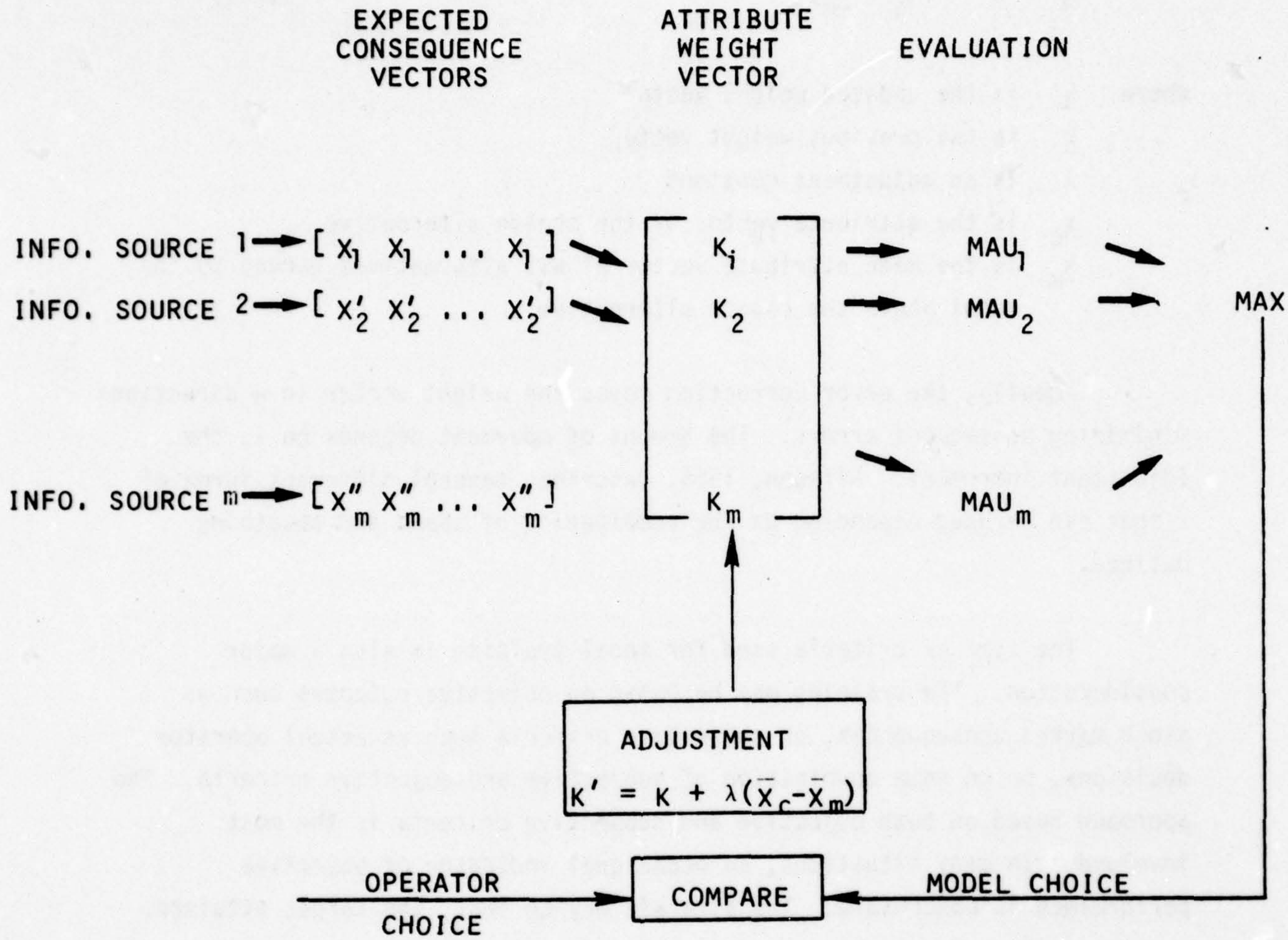

FIGURE 2-2. ADAPTIVE ESTIMATION PROCESS

$$\underline{k}' = \underline{k} + \lambda(\underline{x}_c - \underline{x}_m) \tag{2-4}$$

where $\underline{k}'$ is the updated weight vector

$\underline{k}$ is the previous weight vector

λ is an adjustment constant

$\underline{x}_c$ is the attribute vector of the chosen alternative

$\underline{x}_m$ is the mean attribute vector of all alternatives ranked by the model above the chosen alternative.

Ideally, the error correction moves the weight vector in a direction minimizing subsequent errors. The amount of movement depends on λ, the adjustment increment. Nilsson, 1965, describes several different forms of λ that can be used depending on the combination of speed and smoothing desired.

The type of criteria used for model training is also a major consideration. The training may be based on objective outcomes such as stock market consequences, or subjective criteria such as actual operator decisions, or on some combination of subjective and objective criteria. The approach based on both objective and subjective criteria is the most involved. In many situations, an occasional indicator of objective performance is observable. The aircraft may be lost, the target attained, or some number of subgoals accomplished. In this way, the correctness of a sequence of actions may become objectively known. The utility model would be trained subjectively prior to this by observation of the operator's choices. If the sequence of choices led to an objectively favorable outcome, the trained parameter set would be retained. If the outcome was unfavorable, the parameter set would be returned to the levels present prior to the sequence of decisons. In this way, objective criteria would guide overall training, but the explicit decision-by-decision policy for information management would be subjectively derived.

Of course, the adaptive techniques of estimation described above are warranted only if repetitive decisions are available for training and if the differential weighting of attributes is important. In cases where only a few non-repetitive decisions will be made, off-line estimates of the weights k_i are favored. Here, techniques such as direct estimates, hypothetical lotteries, or multiple regression are used for estimation prior to the mission. It is assumed with these techniques that the system requirements will not change after the estimates.

Questions concerning the importance of differential weighting are more basic. Unit weighting schemes (in which all weights k_i are set equal to 1.0) have been found to be quite effective in certain circumstances. Errors in the model form, positive correlations between variables, and small sample sizes all reduce the predictive capabilities of differential weights compared to unit weights (Einhorn and Hogarth, 1975). Essentially, the more precise and parsimonious the model, the more important differential weights are.

Unit weighting schemes are expected to see only minor application in aiding advanced aircraft operations. Careful selection of attributes minimizes intercorrelations between variables, and the correlations that do occur should tend to be negative. For example, in most cases costly information is generally more informative than inexpensive information, and equipment attrition tends to be negatively correlated with goal attainment. These circumstances favor inferred weight models. Unit weighting schemes should primarily be useful as starting points for estimation, or as strategies for situations in which a great deal of noise is present.

The processes described above potentially form the basis of a decision aiding system. The sequence can be divided into three segments --

modeling, analysis, and execution. Modeling consists of structuring, the definition of the various components of the decision model, and assessment, the determination of the parameter levels. These operations are normally shared in function. The human defines the problem structuring (at least until self-organizing systems are realized) and the computer performs the assessment. The second segment, analysis, may be assigned completely to the computer. This stage involves solving the model to determine its implications, and computing the effects of altering model assumptions. The final segment, execution, is again a flexible function: either man or machine may make the decision. In the early stages of model training, the human would be expected to perform the action with the machine observing passively. Later, with increased confidence in its choices, the computer could either make recommendations to the operator or take over the decision functions autonomously (subject to operator override).

Evidence for the usefulness of the multi-attribute utility formulation and adaptive estimation programs was obtained during the initial year of the program (Steeb, Chen and Freedy, 1977). A simulation resembling control of a remotely piloted vehicle (RPV) was used in this study. Individual subjects navigated the RPV through a changing hazardous environment. In doing so, the operators selected different combinations of information and control allocation. The adaptive model was found to be more predictive of subject's behavior than either a constant, unity weight model or an off-line method of weight estimation. Also, the model was found to be useful in identifying different decision policies or styles.

2.4 The Adaptive Model as a Decision Aid

2.4.1 Behavioral Forms of Aiding.

The adaptive decision model has the potential of improving system performance through the following three means:

(1) Aggregation: The model keeps track of large amounts of data, performs probability update calculations, and computes tree fold-back values.

(2) Smoothing: The model reduces the random noise or error implicit in human response. This smoothing results from the averaging effect of estimation.

(3) Augmentation: Display of recommendations by the adaptive model may serve to increase the operator's decision making power. Observing the model recommendations, the operator may systematically refine his behavior and possibly consider a larger set of factors.

The aggregation or bookkeeping functions of the computer are an obvious aiding device. The decision program systematically gathers and processes information regarding alternatives, outcomes, event probabilities, and objectives. As such it places a rational framework on operator choices.

Smoothing or reduction of random effects in subjective weighting of data is a well-established advantage of linear models. Linear models based on an operator's average behavior typically outperform the actual behavior of the operator (Bowman, 1963; Goldberg, 1970; Dawes and Corrigan, 1974). Aiding by model recommendation of choices and by model-based automation should result in this type of performance enhancement.

The third area of improvement provided by the model, augmentation, deals with sub-optimal decision behavior that is more deep-seated than noise or random effects. Because of cognitive limitations, the operator can consider only a small number of attributes in a decision. In complex situations, he then constructs his own simplified and manageable model of the problem. This is Simon's (1957) "principle of bounded rationality" in which the man's behavior may be consistent with his own simplified model even though not even approximately optimal with respect to the real world.

The sub-optimal behavior resulting from cognitive limitations may possibly be reduced through model-based aiding. Macrimmon (1973) suggested that by operating in parallel with the DM, a model can present decision recommendations based on a normative processing of the circumstances and utilities. The operator's task is then changed to one of evaluation and correction. Freedy and his associates (1976) displayed such model-based recommendations to operators in a simulated task of submarine surveillance. Significant improvements in performance resulted, possibly from the opportunity to consider more complex and effective strategies.

Unfortunately, the parallel, closed loop relationship of man and model engenders some problems of dynamics. With aiding, the decision faced by the operator includes both the attribute patterns of the choices and a normative processing of those patterns. Since this processing is based on his previously observed behavior, it should lead to greater consistency, speed, and effectiveness in recurrent situations. However, it may result in inappropriate recommendations in completely new circumstances. These characteristics are typical of predictive displays. The predictions are only accurate if future behavior can be estimated from previous observations. Thus with a major structural change in the environment, the recommendations may be based on irrelevant data, and could slow the operator's adjustment. Kunreuther (1969) states that this type of lag can be minimized by including only recent decisions or by exponentially weighting the observations according to the age. A recency bias of this type is realized to some extent by virtue of the adjustment mechanism. An additional bias may be necessary in rapidly changing situations.

2.4.2 Aiding Functions. The specific forms of aiding provided by the adaptive model may be classified into three main functional areas: Problem recognition, situation diagnosis, and option selection. The possible contributions to each of these areas are listed below.

Problem Recognition. This aspect of the decison process involves the monitoring of an ongoing action on a set of descriptive dimensions, comparing the set against acceptable limits, and determining that the action is still appropriate to the situation. Outcomes of these processes either initiate a new action, or modify an ongoing action.

Problem recognition is a key function in airborne tactical operations. Aircraft may be programmed to follow a course unless special circumstances arise. Response maneuvers or transfer of control to the supervisory operator may be specified by the multi-attribute decision model. Again, trade-offs between communication costs, potential losses, operator loading, and other factors are made by the model. This function unburdens the operator of repeatedly interrogating the system as to its status. Also, available empirical evidence suggest that men tend to err on the side of conservatism in problem recognition. For example, Vaughan, Virnelson, and Franklin (1964) had experienced Army officers monitor a series of messages that indicated the need to change the axis of advance in a simulated attack scenario. With only one exception, officers did not modify the ongoing action plan nor did they anticipate the possibility of changing the plan in spite of a series of messages indicating this need with increasing urgency. Thus, in some circumstances a automated system for problem recognition may be essential.

Situation Diagnosis. For effective decision making and control functions, the operator must accurately assess and integrate the probability of occurrance of events. Among these estimates are judgments regarding likelihoods of obstacles, detection of communications, possibility of visibility loss, etc. Man tends to be a weak diagnostician when dealing with multiple probabilities. Summarizing results from several studies of clinical diagnosis, Goldberg (1968) concluded that diagnostic judgments are:

(1) unreliable overtime,
(2) unreliable across diagnosticians,
(3) only marginally related either to experience of the man or to his confidence in the accuracy of his judgments,
(4) only slightly affected by amount of available information,
(5) generally of low validity.

In a similar vein, Edwards (1963) presented evidence from non-clinical studies that man is a relatively good probability estimator for single items, but poor at aggregating a number of probability estimates to form a conclusion. Additional evidence and discussion of this misaggregation effect are provided by Slovic and Lichtenstein (1971) and Rapoport and Wallsten (1972).

The decision model performs many of the probability aggregation functions normally required of the operator -- frequency tabulations, probability update calculations, etc. The program performs these calculations more rapidly, reliably and accurately than is possible manually. The operator of course, may still provide inputs for the probability programs in the form of single item prior and conditional probabilities.

Option Selection. The options open to the decision maker are information to acquire and actions to select. These options are interdependent, as noted earlier in section 2-2. The value of information is due to its impact on the subsequent action decison. Each of these choices, information acquisition and action selection, is tied to maximization of overall expected gain or utility.

For the operator, simultaneous consideration of multiple alternatives portrayed against multiple criteria quickly becomes too complex for easy resolution. For example, Connolly and his associates conducted a series of experiments at Hanscomb Field to assess the appropriateness of weapon selection decisions by experienced Air Force officers in a simulated air defense environment (Connolly, Fox and McGoldrick, 1961; Connolly, McGoldrick, and Fox, 1961). Although instructed to use three criteria in the selection of weapons to targets (minimize damage to defended area, destroy maximum number of threatening objects, and conserve counter-weapons), actual selection reflected a disproportionate weighting of the three factors. Again, computer-based aggregation of factors is indicated. The coming sections describe the means by which the forms of aiding described here can be applied to the problems of information selection in tactical airborne operations.

3. DECISION AIDING IN ADVANCED AIRCRAFT OPERATIONS

3.1 General

The selection and presentation of information in tactical airborne systems introduces some special problems that compound those mentioned earlier. The operator must, under considerable time stress, weigh the probable usefulness and costs of a variety of competing forms of information -- mission status, track data, environmental information, aerodynamic functioning, etc. These moment-to-moment judgments must often be based on subjective factors, since the decision is normally too complex and dynamic to be analytically tractable.

The adaptive programs described earlier hold a great deal of promise for aiding in advanced aircraft operations. Tactical airborne systems typically require consideration of voluminous amounts of relevant and irrelevant information. At the same time, severe time stresses and interfering tasks can degrade the information integration processes. To reduce the operator load, combat aircraft typically have sophisticated autopilot and weapon control systems. These systems are expected to be extendable to include functions of information evaluation and management, since they take into account the key factors of environmental state, vehicle state, and task objectives. The following sections describe the definition, structuring, and implementation of adaptive decision models in the context of tactical airborne operations.

3.2 Information System Characteristics

The typical advanced aircraft mission can be defined by a series of mission phases, much like the stages of the RPV supervision task analyzed in the initial year (Steeb, Chen and Freedy, 1977). The phases can be characterized by the danger or frequency of threats, the time available for decision making, and the options and characteristics of information concerning the aircraft and the environment.

The information available at a given time is dependent on the environmental situation, the sensor characteristics, the data base content, and the display capabilities. The information itself may consist of data regarding weather conditions, aerodynamic status, target track, ECM, and mission status.

The costs of acquiring information result from the sensor characteristics, the direct and indirect costs of sensor deployment, information processing and display, and the amount of attention the operator can contribute. The direct costs of information acquisition include such factors as energy expenditures and equipment expenses. Indirect costs include increased possibilities of detection and countermeasures. The available operator attention, finally, is defined by the task demands and the individual capabilities of the operators.

The costs and payoffs associated with the various possible outcomes vary with mission phase. The consequences are defined not only in terms of attrition of equipment and attainment of objectives, but also as a function of organizational policy and procedures. The relative importance of fuel expenditures, vehicle survival, countermeasures, etc., change as the mission objective is approached, attained, or past. The relative importance of these factors must be assigned by the human operator or by the command group.

Available time for decision making varies throughout the mission as a direct function of the varying vehicle speed, altitude, and surrounding weather conditions. Altitude, cloud cover and ECM determine the distance that obstacles, navigation points, or targets can be observed. The speed then determines the available time. Decision time can be expected to influence the amount of information that can be processed and the probability distribution of the possible consequences.

In sum, the selection of information and control to allocate to the supervisory human operator is a complex and dynamic decision. The decision maker must continually weight the probable usefulness of the information against the costs of acquiring it. Since this decision is especially difficult, the costs and benefits are both multi-dimensional and probabilistic.

3.3 Structure of the Information Seeking Model

3.3.1 Information Management Functions. The major information management functions faced by the operator are diagramed schematically in Figure 3-1. The information available consists of data regarding the aircraft, the targets, the environment, and operator and system capabilities. The information is then used by the operator to perform supervisory control actions.

The information and control choice sequence is that diagramed earlier with the decision tree of Figure 2-1. This diagram is repeated with labels representative of tactical airborne operators in Figure 3-2. The multi-attribute utility formulation provides a useful basis for structuring both the information and control decisons. The specific steps of the modeling process are outlined in Figure 2-3. The figure shows the two sides of the modeling problem, probability estimation and utility assessment. The upper portion of the figure details the processes of probability estimation. These include delineation of the possible states of the environment, evaluating the current level of uncertainty concerning states,

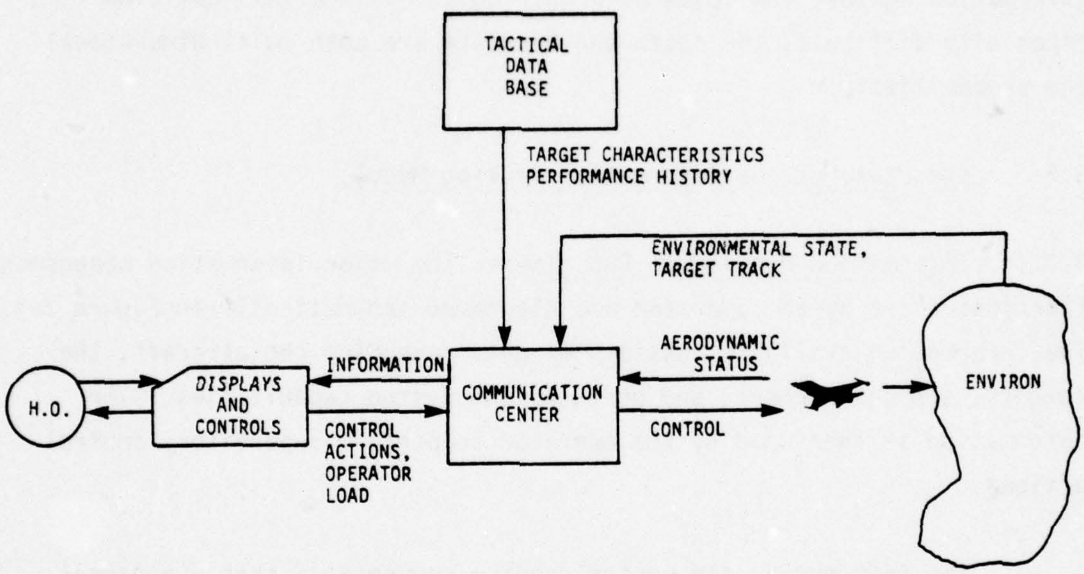

FIGURE 3-1: MAJOR INFORMATION MANAGEMENT FUNCTIONS

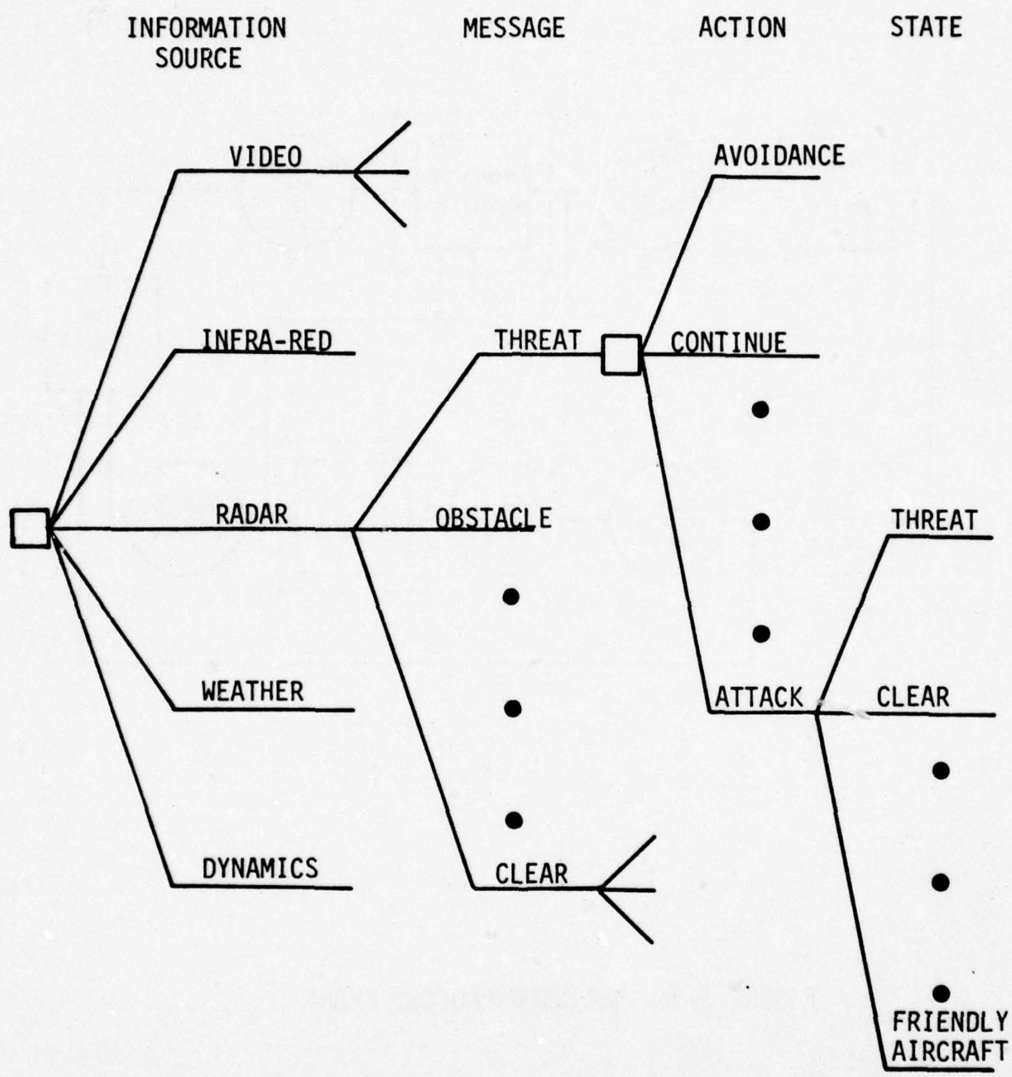

FIGURE 3-2: DECISION TREE FOR INFORMATION SEEKING IN TACTICAL AIRBORNE OPERATIONS

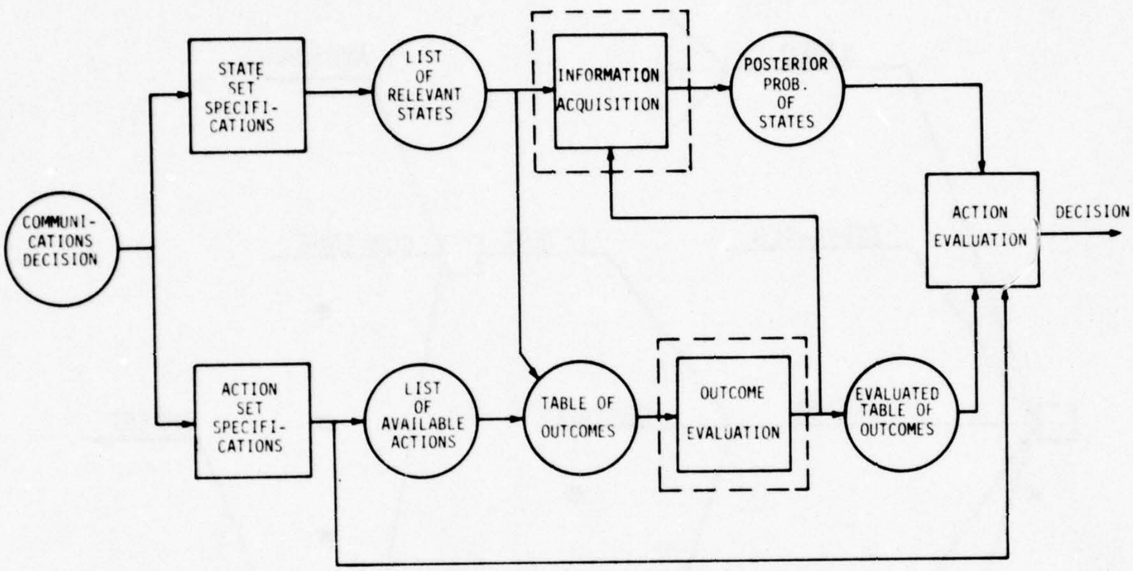

FIGURE 3-3: DECISION PROCESS CHART

selecting information to reduce the uncertainty, and revising the probability estimates in light of the new data. The lower portion of the figure is concerned with outcome evaluation or utility estimation. Here the levels and importance weights for each dimension of consequence are determined.

The key element in the probability estimation sequence is the information acquisition stage (enclosed by dotted lines). Figure 3-4 elaborates this stage, showing the steps that go into the choice of information and the subsequent incorporation of the datum into the situation estimate. The upper portion of the figure deals with the information source selection. The characteristics of the various available sources are determined by observation and analysis. This estimation of the characteristics of the information sources is accomplished by successive comparisons of messages received and subsequently observed states. The choice of information source is then made according to the potential impact of the information on the prior probability estimate. Once a source is selected and a datum observed, the information is incorporated into a revised situation estimate through Bayes' rule:

$$P(z_h|y_j) = \frac{P(y_j|z_h) \cdot P(z_h)}{P(y_j)} \qquad (3\text{-}1)$$

where $$P(y_j) = \sum_i P(y_j|z_h) \cdot P(z_h)$$

$P(z_h|y_j)$ is the probability of state z_h being present given that message y_j was received.

The other major modeling process is utility assessment or outcome evaluation. The possible combinations of actions and states are enumerated

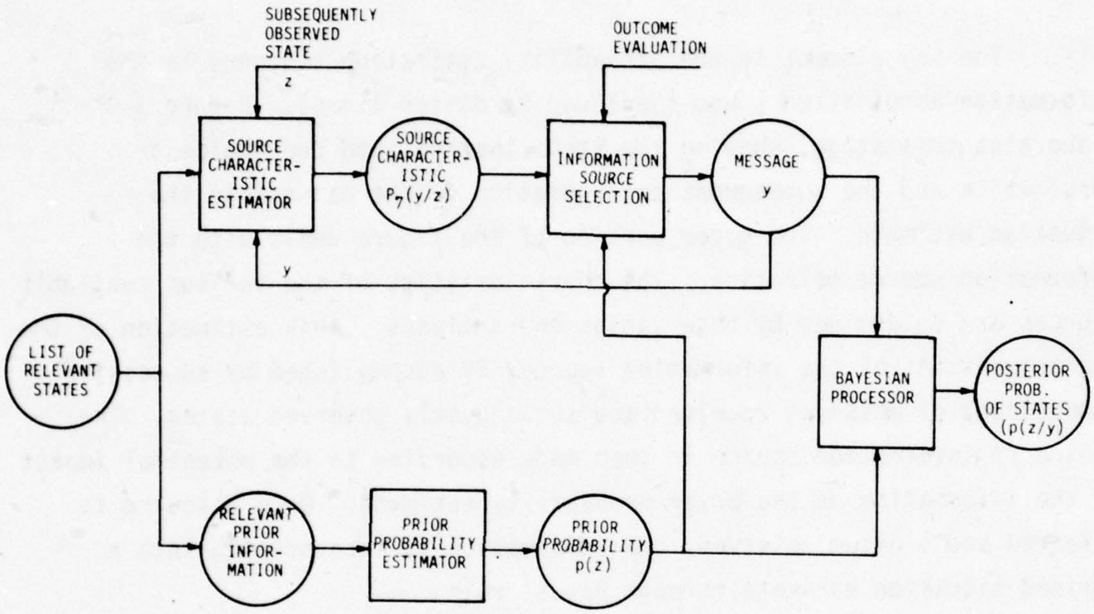

FIGURE 3-4: PROCESSES INVOLVED IN PROBABILITY ESTIMATION

(This is an elaboration of the "Information Acquisition" block of Figure 3-3) off-line prior to a mission. The problem is then to assign consequence levels and importance weights along a predefined set of dimensions. Figure 3-5 elaborates this process. The first step is the selection of an independent, exhaustive, and predictive attribute set. The attributes are the various constituent aspects of the consequences. Each combination of information, action and outcome is associated with a set of attribute levels. This is done by observation and adjustment, just as in the determination of information source characteristics. Scaling procedures are applied to the raw consequence dimensions to arrive at normalized values. Each attribute is scaled so that its plausible range spans zero to one. These processes result in a specification of the parameters of the basic multi-attribute formulation:

$$E\,[u(x)]_s = \sum_{K=1}^{M} P(z_k) \sum_{i=1}^{N} K_i \; u_k\,(x_{ijk}) \qquad (3\text{-}2)$$

where

$E\,[u(x)]_s$ is the expected utility of information choice s.

$P(z_k)$ is the probability of state k with this information choice

K_i is the importance weight for attribute i, and

x_{ijk} is the level of attribute i associated with action j and state k

The following sections will develop some of the specifics of the modeling cycle.

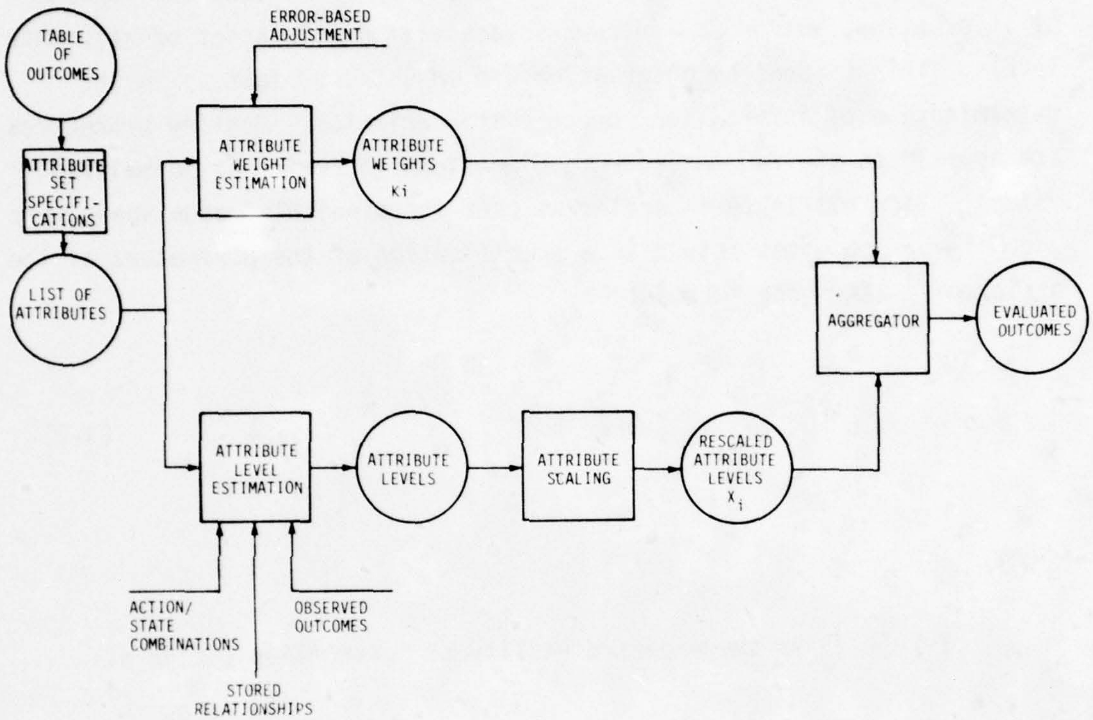

FIGURE 3-5: PROCESSES INVOLVED IN OUTCOME EVALUATION

(This is an elaboration of the "Outcome Evaluation" block of Figure 3-3)

3.3.2 Attribute Development. The attributes of an information seeking decision are dimensions of consequence that are common to all tips of the decision tree (shown earlier in Figure 3-2). These dimensions may include communications costs, equipment losses, goal attainments, future effects, and other factors. In the end, the constituent effects will be weighted and aggregated together to arrive at an overall evaluation of an outcome.

The actual choice of the attribute set is extremely important. Dawes (1975) states that the choice of factors to include is probably of greater impact than the determination of the model form. Desirable characteristics are accessibility for measurement, independence, monotonicity with preference, completeness of the set, and meaningfulness for feedback. Monotonicity, in this content, implies that an increase in the attribute level always results in an increase in preference. If the attribute levels are monotonic, a simplification is possible. (Fisher (1972) and Gardiner (1974) note that a straight line approximation to the utility function results in minor losses of model accuracy. The estimated utility (ignoring uncertainty for now) is then a weighted linear combination of attribute levels:

$$U(a_z, z_h) = \sum_i k_i x_{ihk} \qquad (3\text{-}3)$$

where $U(a_z, z_h)$ is the utility of state h occurring with action z, k_i is the importance weight for attribute i, and x_{ihk} is the level of attribute i associated with state h and action k.

Information costs may comprise attributes of special note. Often, the benefits of an information acquisition are simply weighted against the costs of acquiring the information. If a net gain is anticipated, acquisition of the information is considered justified. Often, though, the costs themselves are multidimensional, comprising energy costs, time delays, equipment expenditures, and risks of detection. The scaling, weighting, and aggregating of these costs may be most easily performed in combination with all of the non-cost attributes -- tactical gains, political impact, etc. Then, trade-offs among each of the factors may be performed in a single, consistent operation.

A candidate set of attributes might contain factors from five areas:

(1) Communications Costs - The expenditures associated with use of the information sources. These may include requirements of energy, equipment, and operator attention.

(2) Equipment Attrition - Consequences concerning the integrity of the vehicle. Included are fuel expenditures, system damage, and vehicle loss.

(3) Objective Attainment - The degree of accomplishment of the mission objectives. Target goals may be the area reconnoitered, adversaries dispatched, and political impact obtained.

(4) Dynamic Effects - The future consequences resulting from the current actions. These consequences may include effects on subsequent action choices, availability of future information, and changes in the environment resulting from the action.

(5) Subjective Needs - The operator may have propensities for obtaining (or refusing) information beyond that called for by the above factors. These preferences relect needs of task continuity, maintenance of load, or other idiosyncratic factors.

A useful consequence set might contain a single dimension or attribute from each of these categories. In fact, five attributes appears to be an upper limit to the number of factors a decision maker can effectively consider (V. Winterfeldt, 1975). If several factors contribute to one consequence dimension, these factors should be combined using a single common scale -- dollars, ship-equivalents, fuel quantity, etc.

Each of the attributes -- communications costs, vehicle losses, etc., -- must be scaled with interval properties along a set range. The least desirable consequence that may occur is assigned a level of zero on the scale. The most desirable consequence is assigned a level of one. The weighting factors k_i should also be normalized so that the overall worst combination of factors results in a value of zero and the overall best combination a value of one.

A special situation occurs with probabilistic attributes. Assuming risk neutrality, probabilistic consequences may be computed according to their expected level. For example, the vehicle loss attribute may have three possible levels, each with a different probability of occurrence. The expected value is computed by the following additive expression:

$$E(x_{ij}) = \sum_{k=1}^{3} P(z_k)x_{ijk} \tag{3-4}$$

where the parameters are defined as in Equation 3-3. Once the attributes are defined and their levels are determined, the aggregation rule must be identified. The attributes - costs, losses, delays, future impacts, etc., - may combine in an additive, multiplicative, or more complex fashion (see Keeney and Raiffa, 1975, for a description of some of the more popular formulations). For the work here, the simple additive form, exemplified by Equation 3-3 appears to be the most suitable. The additive form is robust, intuitively easy to understand, and simple. Also, the linear form of the additive will be seen to be amenable to estimation by pattern recognition techniques.

3.3.3 Consequence Level Determination. The actual level of each of the attributes for a given outcome can be determined by mappings between predictive features and the attributes. Predictive features must be identified which are accessible to an onboard program and capable of determining the consequence levels. Mappings between the predictive features and the attributes are either pre-established or determined by observation and adjustment.

The data available to the decision program are:

(1) Directly sensed information concerning the environmental state (weather, terrain, ECM, target track).

(2) The vehicle state (velocity, fuel, autopilot capability).

(3) The information system characteristics (capacity, noise, cost).

(4) Tactical data (technical characteristics of own and enemy aircraft, sensors and weapons; information about the operations area).

(5) Action alternatives (control responses, weapon deployment).

(6) Operator capabilities (attention, load).

A manageable subject of these features must be determined. The consequence mapping can then be refined by comparison of the predicted and actually observed consequences. The mapping can be developed either by prior definition, by regression, or by the pattern recognition techniques described in the coming section.

3.3.4 Weight Assessment. The method of assessment developed in the initial year's study -- adaptive estimation using pattern recognition -- is well suited to the information evaluation and management problem. The goal is to estimate the operator's decision making policy by observation of his choices. The procedure was diagramed earlier in Figure 2-2. First, expected consequence vectors associated with each information choice are input to the model. These consequence vectors are dotted with the weight vector, resulting in evaluations along a single scale. The maximum expected utility choice is determined and compared with the operator's actual choice. If a discrepancy occurs, the weight vector is adjusted according to the procedure represented by Equation 2-4. Ideally, the error correction moves the weight vector in a direction minimizing subsequent errors. A detailed description of the structure and dynamics of the estimation procedure is given in our previous technical report (Steeb, Chen and Freedy, 1977).

An alternative, non-adaptive means of weight assessment is possible through use of direct elicitation. The operator is familarized with the task situation and then presented with a series of choices such as that shown in Figure 3-6. Here one attribute (cost) is assigned an arbitrary weight and each remaining attribute is compared to it. The comparisons between attributes are tied to the possible range that each attribute spans, hence the use of the anchored, worst-to-best scales shown in the figure. The estimation procedure is as follows: If a shift in cost of an alternative from 16 points to no cost has a value of 10 (this is an arbitrary baseline), what is the value of a shift in delay of 6 seconds to zero delay? A value

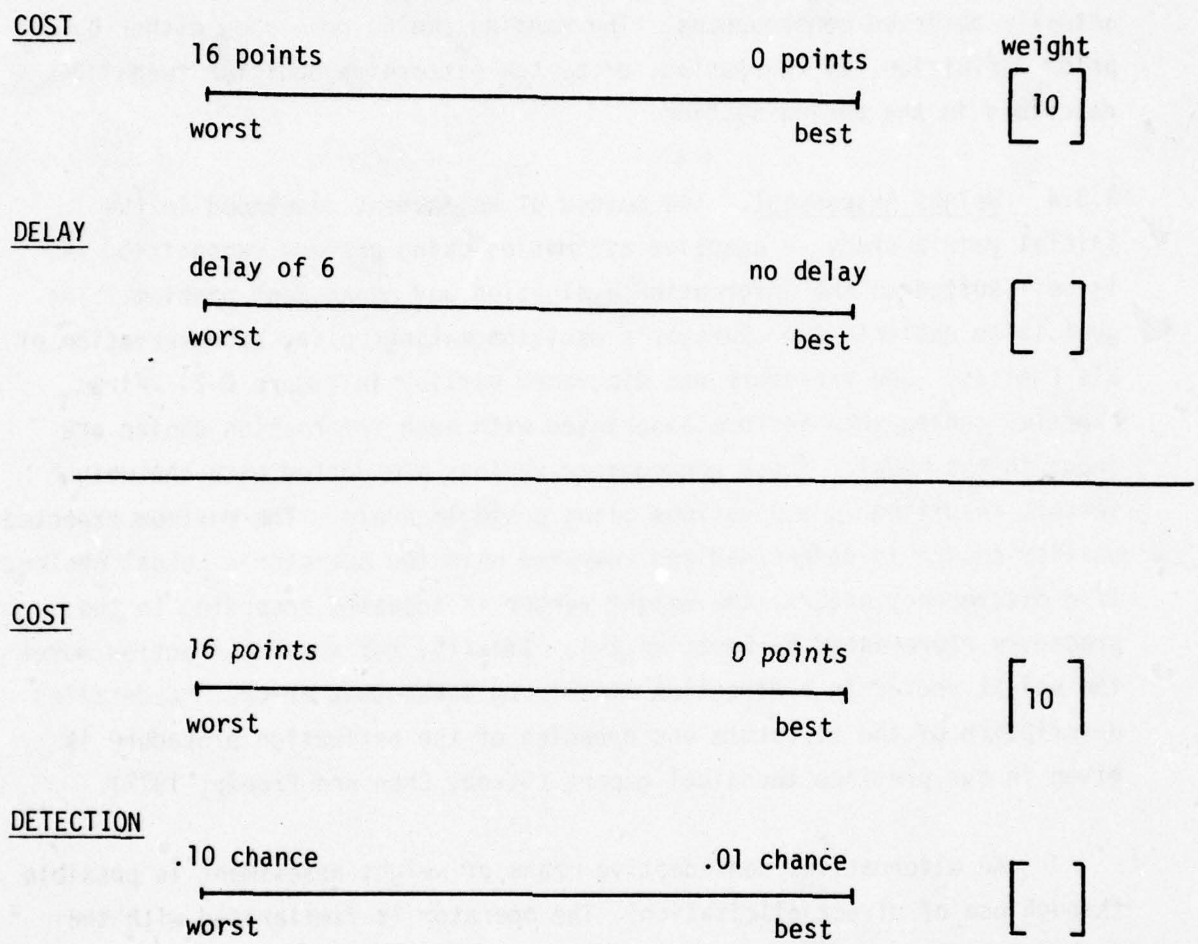

FIGURE 3-6. DIRECT ELICITATION OF IMPORTANCE WEIGHTS

of 20 would mean that this shift in delay is twice as important as the cost shift, a value of 5, half as important. Similar comparisons are made between the baseline attribute (cost) and each remaining attribute. In the end, all weights are normalized so as to sum to 1.0. This procedure is representative of many direct elicitation approaches, and exhibits some of the problems associated with these techniques - hypothetical choices, use of extreme points, interference with the task, etc. Nevertheless, it is a useful means of estimation in many situations. A experimental comparison of the adaptive technique and direct elicitation method will be found in Chapter Four.

3.3.5 Probability Estimation. The major probability parameters requiring estimation are the prior probabilities $P(z)$ and the conditional probabilities $P(y|z)$. The priors are the probabilities of state z in a particular situation. The conditional probabilities deal with the likelihood of receipt of message y if state z is present. Both of these forms of probabilities can be estimated from frequency counts.

A second area of uncertainty concerns the consequence levels associated with a given message and state. These are the performance probabilities and are derived from stored data: Detection range, target hardness, personnel performance, system reliability, guidance system accuracy, etc. The probability of outcome given the message received can be computed for each set of actions. Comparison of the messages received, actions taken and the consequences subsequently observed provide the necessary data.

3.3.6 Level of Detail. The level of detail handled by the model is basically a problem of efficiency of categorization. Choices of the fineness of distinction of information modes, messages, and states involves a trade-off the model complexity (and processing time) against degree of specification of aiding. For example, the information available may be classified by context element (threat identity, weather formation, malfunction location, terrain characteristic, etc.) or by source (radar, infra-red sensor, video, tactical data base, radio, etc.). Similiarly, the messages and states may be represented in the model as specific details of threat position, course, speed and identification, or more globally as specific threat presence or absence. Of course, separate prior and conditional probability estimates must be maintained for each state represented in the model.

Much of the question of level of detail was to do with the concept of payoff relevance, a term introduced by Marschak (1963). The partitioning of the information space must result in differences in (1) the existing representation of the decision situation, (2) the actual decisions made, and (3) the utility resulting from the changed decisions. Information may be ineffective in changing the situational representation and resulting decisions because the data is too coarse or too fine. Information that is too coarse fails to distinguish between effectively different states of nature for at least one of the alternative actions. Information that is too fine differentiates between states having identical payoffs for all actions. Effective information -- data that is not too fine or too coarse -- is termed by Marschak to be payoff relevant. In the experimental application of the model, an attempt will be made to structure the model so that the cost of the chosen level of detail is commensurate with the benefits.

3.4 Aiding in Advanced Aircraft Operations

3.4.1 Forms of Aiding. It was noted earlier that three major forms of aiding are possible once the operator's decision policy is estimated: (1) system evaluation and design, (2) automated management of information, and (3) operator training. This section will describe in more detail the potential of model-based aiding for tactical airborne systems. Recounting briefly, system evaluation and design entails the determination of each system component's contribution to information value (satisfaction of operator needs). Specification of system configuration commensurate with task demands and individual operator needs is then possible. Automated management of information is the moment-by-moment control of display content and format by selection among available information. Operator training, finally, involves the use of policy feedback to train the operator to make effective information and control decisions. The first two of these uses of the decision model, system evaluation and automated information management, will be described in greater detail in the following sections. Model-based training is presently outside the scope of this work.

3.4.2 System Evaluation. Two types of evaluation are possible using the information extracted from the information value model: direct contribution and marginal contribution. Each of these evaluation measures is described below.

Direct Contribution. This is the user-specific value of a given information source in a given task situation. As such, it is a simple aggregation of components, weighted by the user's policy:

$$\text{info value}_{jks} = \sum_{\substack{\text{attributes} \\ i}} k_{ij} \, \overline{x}_{ik} \tag{3-5}$$

Where info value $_{jks}$ is the aggregate value of source s to user j in situation k, k_{ij} is the importance weight of attribute i to user j; and k_{ij} is the mean level of attribute i in situation k. This formulation is useful when each information source contributes to a different task - threat detection, navigation, etc. The direct contribution measure does not deal with information sources having overlapping function.

<u>Marginal Contribution</u>. In a group of information sources with overlapping function, the information value of one source can be calculated with the following expression:

$$\text{information value}_{jks} = \sum_{\substack{\text{attributes} \\ i}} k_{ij}\, x_{ik} - \max_{\substack{\text{over} \\ \text{remaining} \\ \text{sources}}} \sum_{i} k_{ij}\, x_{ik} \qquad (3\text{-}6)$$

This is the incremental value of a source over the next most highly valued source. The summation of all positive contributions for a given source indicate the source's value in the particular task situation.

Using either the direct or marginal measure of information value, the mission value of an information source can be calculated as the summation across the probability distribution of task situations.

$$\text{info value}_{js} = \sum_{k} \text{prob (situation } k) \cdot \text{information value}_{jks} \qquad (3\text{-}7)$$

This provides an overall, user-specific index of information value.

3.4.3 <u>Automated Management of Information</u>. The information value model described in section 3.3 can be used directly for management of information. The multi-attribute utility model represents the policy of the specific user, it has access to the factors characterizing each information choice, and it can be linked to the onboard information control system. The model can thus be configured to automatically scan the available information sources, select the immediately most useful source, and display it to the operator. The following sections describe an initial application of such an aiding program.

4. EXPERIMENTAL STUDY

4.1 Overview

An experimental study was performed to test the effectiveness of the adaptive decision model in information management. An advanced aircraft simulation was developed, replacing the RPV simulation used in the initial studies. (Steeb, Chen and Freedy, 1977.) Individual subjects were required to pilot a simulated aircraft in a changing, hazardous environment. In doing so, the operators were able to select from a variety of forms of information concerning the multiple threats encountered, and take either evasive or aggressive actions. Performance comparisons were made in the study between adaptive and non-adaptive techniques of estimation of model parameters.

4.2 Hypotheses

The following experimental hypotheses were tested:

(1) The multi-attribute model can be used to accurately evaluate the effectiveness of different information system configurations under a variety of task conditions.

(2) Automated management of information by the adaptive model results in performance superior to that obtained with the off-line model and superior to that obtained with manually selected information.

(3) The improvement of aiding in either form of automated information management will be enhanced in conditions of higher speed stress.

(4) Operators will be more accepting of automated information management in conditions of high speed stress and adaptive estimation.

4.3 Task Simulation

The task simulation is patterned after an important and representative information acquisition task -- multiple threat intercept operations in advanced aircraft. The simulation is an adaptation of the remotely piloted vehicle supervision task employed in the previous study. (Steeb, Chen and Freedy, 1977.) The format of the display is similar to that used previously, but threats replace the obstacles, and the actions open to the operator are more varied, encompassing both avoidance and attack options. Also, a wider variety of information sources are available to the operator. Briefly, the simulation requires the operator to control an advanced aircraft in a hazardous mission. Threats of uncertain capability and location are encountered repeatedly. The operator has the option of accessing several forms of information about the threats. The forms of information differ in threat discrimination capabilities, transmission costs, processing delays, and potential of detection.

4.3.1 Displays and Controls. The simulation uses a computer-generated CRT display, illustrated in Figure 4-1. The environment and aircraft are shown as they would be in a moving-map display. Sets of threats appear at random positions at the upper edge of the display and move downward at a constant velocity. The operator can move the vehicle symbol horizontally to one of eleven different pathways to avoid the threats, or he can remain on course and take an aggressive action against one of the threats. The actions open to the operator are primarily decision making in nature. Dynamics of control are minimized since the threat and vehicle velocities are held constant.

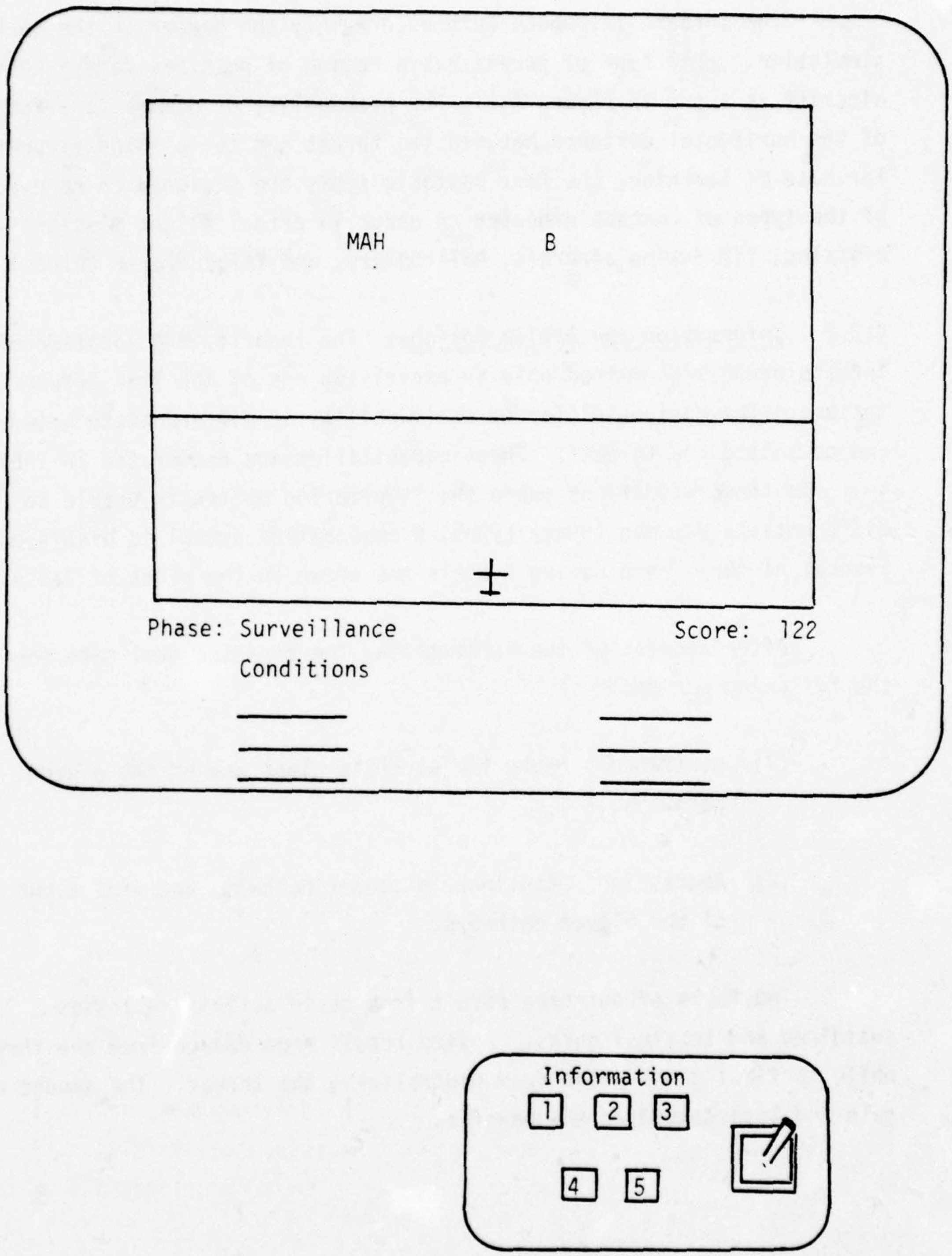

FIGURE 4-1: SIMULATED DISPLAY AND COMMUNICATIONS PANEL

The threats introduce both uncertainty and danger to the task simulation. Each type of threat has a region of possible damage to the aircraft as shown in Figure 4-2. The probability of damage is a function of the horizontal distance between the threat and the piloted aircraft. For ease of learning, the four obstacle types are designed to be evocative of the types of contact expected to occur in actual flight missions -- missiles, fixed-wing aircraft, helicopters, and false alarms (birds).

4.3.2 Information and Action Options. The identity and location of the threats can be determined only by exercising one of the five information options. The options differ in their ability to differentiate between and to locate the threats. These capabilities are enumerated in Table 4-1. In those situations where the information option is unable to differentiate between threat types, a combination symbol is displayed. Several of these combination symbols are shown on the right of Table 4-1.

After receipt of the information, the operator must take one of the following actions:

(1) Avoidance - route the aircraft along one of the eleven pathways.

(2) Aggression - continue in center pathway, and fire along one of the eleven pathways.

Two forms of outcomes result from these actions -- losses sustained and tactical gains. Losses result from damage from the threats, while tactical gains arise from neutralizing the threat. The amount of gain and loss depend on the payoffs.

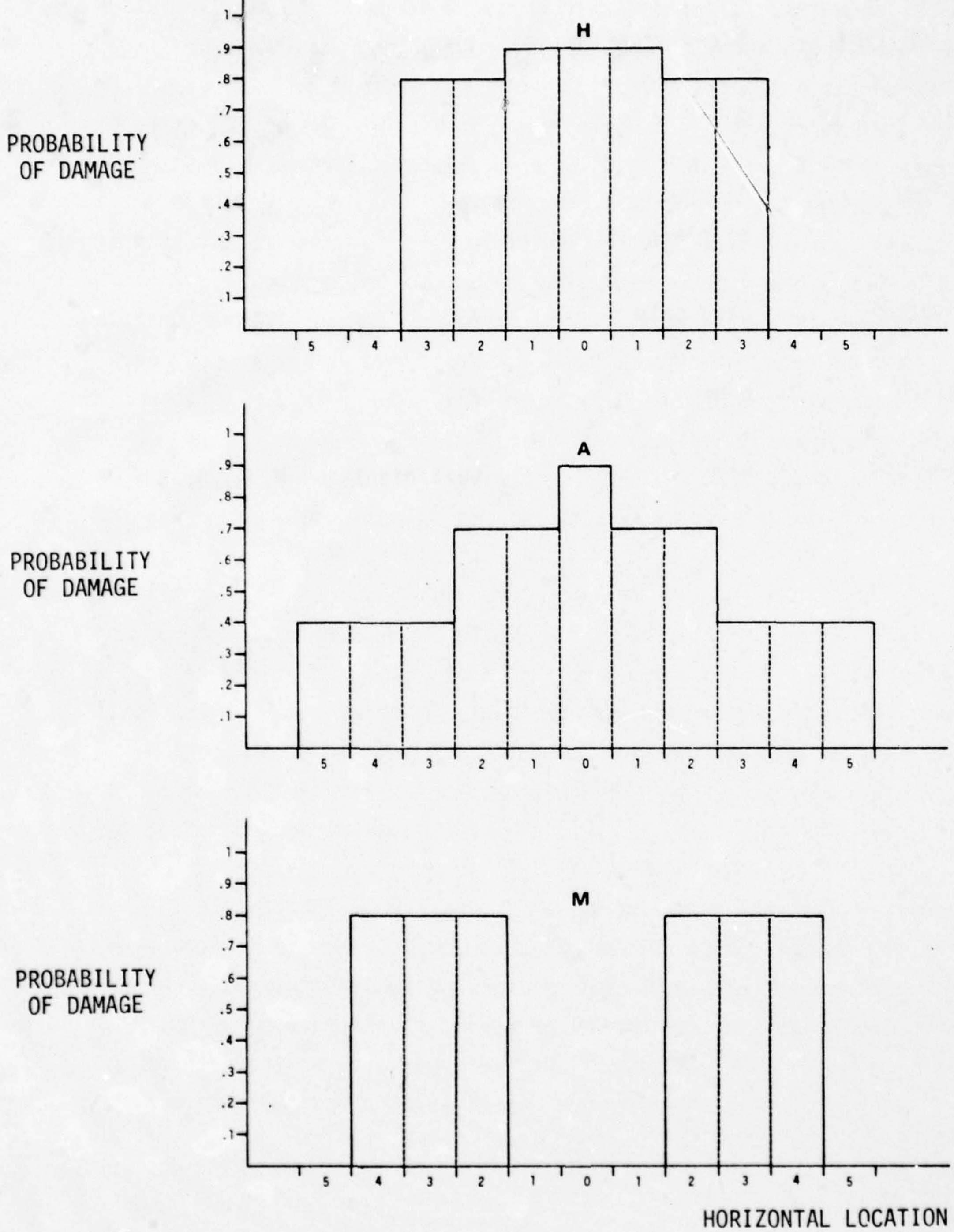

FIGURE 4-2: THREAT CHARACTERISTICS:
HELICOPTER (H)
AIRCRAFT (A)
MISSLE (M)

TABLE 4-1

Information Type	Discrimination	Location	Symbols
1. Full	All	All	M, A, H. B
2. Outline	All but airplane/helicopter	All	M, AH, B
3. Biological	Bird only	All	MAH, B
4. Location	None	All	X
5. Left/right	All	Left/right	M, A, H, B

Sequence. The task consists of a series of similar, connected decisions. Prior to the appearance of any threats, the operator is appraised of the circumstances surrounding the upcoming decision. He must then make an information selection by pressing one of the buttons shown in Figure 4-1. A set of two threats is presented at the top of the screen and moves downward. If "full" information is selected, the differentiated symbols in their proper location move down the screen. If "outline" information is selected, the missile and bird symbols are differentiated, but helicopters and airplanes are represented by a single, non-differentiating symbol (AH). Similarly, "biological" information will use a single, non-differentiated symbol to represent either missile, airplane, or helicopter. "Location" information provides no discrimination. A symbol denotes the location but not the identity of threats. "Left/right" information finally, discriminates the obstacles using the standard symbols, but locates them only as lying in the left of right half of the screen.

The task moves on continuously, just as an airborne mission does. If the operator does not select an information choice in the time allocated (about 5 seconds), location information is provided by default. Following information receipt, the operator must make an action selection before the threats reach the decision limit (a line approximately 2/3 of the distance down the screen).

4.3.3 Situational Conditions. The stages of an aircraft mission can be characterized by such factors as danger, difficulty, system reliability, and communications security. Accordingly, the task simulation was designed to include many of the same factors. The situational conditions are not considered to be experimental variables, but are factors contributing to task complexity. The conditions are:

(1) Degree of danger -- This is the distribution of possible threats in a given phase. A vector of prior probabilities of occurrence of the 4 threat types is assigned to each phase.

(2) Costs -- A different cost is assigned to each information choice. This is the number of points expended for use of the information.

(3) Detection -- The increased danger on the succeeding decision due to use of a given information source. An additional probability of loss is associated with each of the threats.

(4) Delay -- The delay in seconds before actual display of the information. This may also be quantified as the percent of the distance to the action limit before the information is displayed.

(5) Information Accuracy -- The percentage of information transmissions having inaccuracies. Inaccuracies in location will be present on a specified percent of the decisions.

(6) Payoffs -- Different payoffs in points are made for avoidance of or damage sustained from the threats, and for successful or unsuccessful aggressive actions toward the threats. Each of the payoffs vary phase-by phase.

The presentation of conditions is organized into three distinct mission phases -- cruise, surveillance, and aggression. Each phase has set levels of danger, detection, payoffs and information accuracy. For variability, the costs and delays are varied smoothly and periodically within each phase. All conditions are displayed to the subjects. The mission phases and their associated conditions are:

(1) Cruise: Low danger situation with high accuracy information available.

(2) Surveillance: High danger situation favoring avoidance actions; high cost, low accuracy information is present.

(3) Aggression: High danger situation oriented toward aggressive actions; medium accuracy information is present.

4.4 Decision Model

4.4.1 General. The decision faced by the operator is a two-stage information/action sequence, as shown in Figure 4-3. The decision space is fairly large, resulting from the five possible information choices, 22 subsequent action choices (avoid or attack along each of the 11 pathways), and 330 possible states (combination of threats). A variety of multidimensional consequences result from the resulting space, stemming from the various combinations of outcomes, costs, payoffs, delays, and future impacts.

A purely analytical formulation of this is intractable, just as it is for most operational information seeking decisions. Categorization is an obvious means of reducing the complexity of the decision. Here those elements in the decision similar in consequence can be classified together.

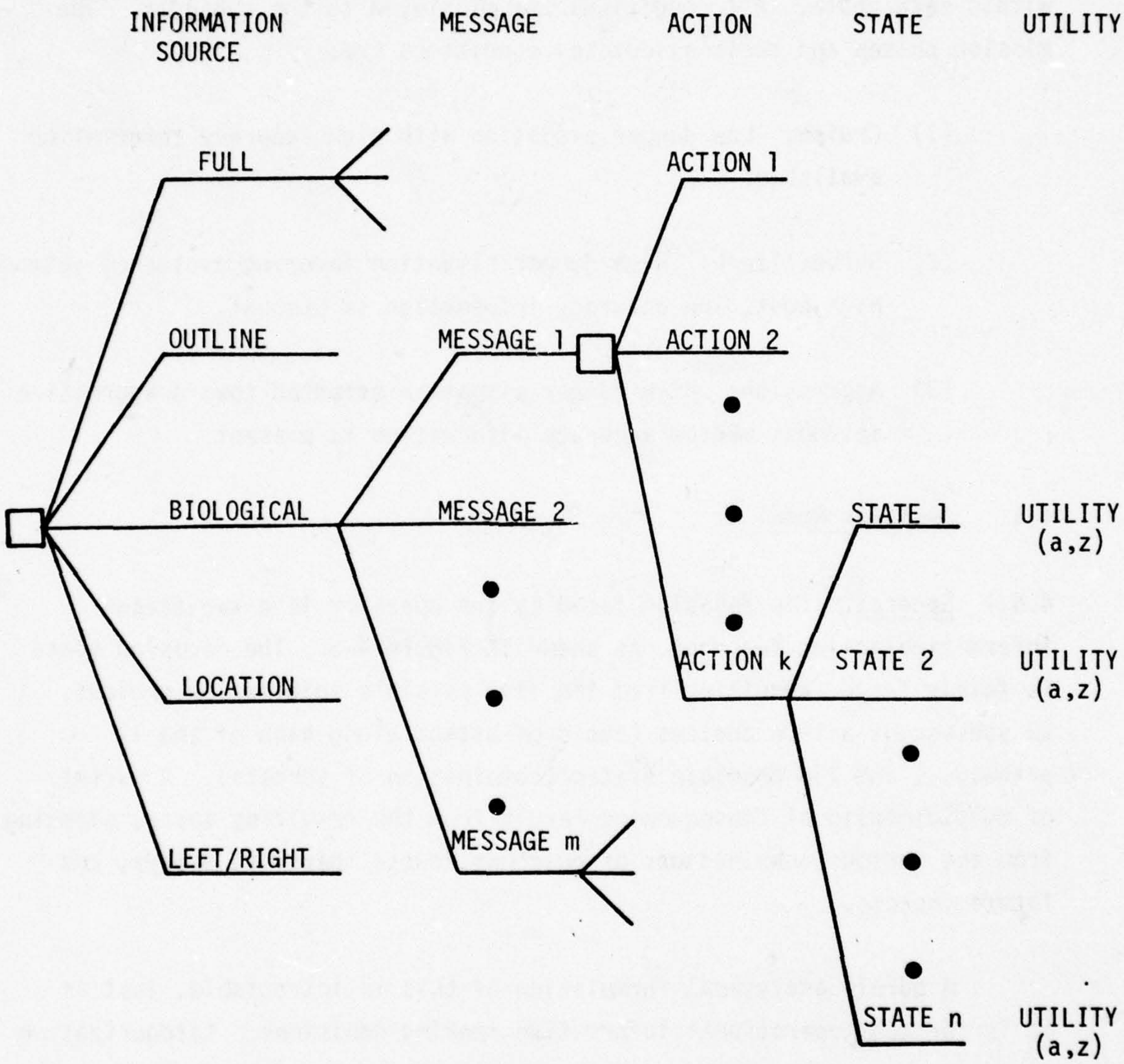

FIGURE 4-3: COMPLETE DECISION TREE

For example, the number of states can be reduced from 330 categories to 6 categories by classifying according to threat combination (ignoring specific location). The probability of each message and state then can be calculated from the prior probabilities of each of the threats and the information source characteristics. The actions can be similarly categorized as avoid or attack without regard to location. Probabilities of each outcome type -- avoidance, damage, missed attack, and hit -- can be established by observed frequency. To do so, a probability estimate must be associated with each combination of information, message, action, and state. After categorization, 90 such combinations are present. These probabilities were determined from a series of pilot system tests, and were intended to be representative of the performance of the typical subject. Estimates specific to each subject were not made. The consequence levels (the attribute level vector) associated with a given information choice in a given situation are calculated by folding back the decision tree. The favored action choice after receipt of a given message is determined in the same fashion.

4.4.2 Decision Attributes. *Five consequence-related attributes are* employed in the decision model. The attributes are the following:

(X_1) Cost - The cost of the communication in points (costs ranged from 0 to 15 points).

(X_2) Delay - The time in seconds before display of the information (delays ranged from 0 to 4 seconds).

(X_3) Detection - Increase in the probability of damage on the subsequent decision (the probability increase ranged from 2 to 10 percent).

(X_4) Vehicle loss - Expected (probability weighted) level of damage to own vehicle (range: 2 to 14 points).

(X_5) Offensive gain - Expected level of damage inflicted on adversary (range: 4 to 10 points).

X_4, the vehicle loss attribute is computed according to the following expression:

$$X_4 = \sum_{\substack{\text{message} \\ y}} \sum_{\substack{\text{action} \\ a}} \sum_{\substack{\text{state} \\ z}} \{P(\text{avoid} \mid y,a,z) \cdot \text{Payoff (avoid)}$$

$$-P(\text{damage}) \mid y,a,z) \cdot \text{Payoff (damage)}\}$$

X_5, the offensive gain attribute, is calculated in an identical manner using the probabilities and payoffs for hit and miss.

4.4.3 Weight Estimation. Two forms of weight estimation were employed in the study -- adaptive estimation from observed behavior and off-line estimation from direct elicitation. Adaptive estimation was performed using the pattern recognition method described in Secion 3.3.4. Prior to the experimental session each subject experienced a training session of three sequences of the three phases (cruise, surveillance, and aggression). A separate 5-element weight vector was maintained for each of the three phases. These three vectors were then "frozen" for use in the automated information management sessions experienced later.

Off-line estimation followed the training session and took the form described in Section 3.3.4. Trial experiences with the direct elicitation procedure demonstrated that the subjects were not able to produce different weight vectors for each phase, but rather followed a single overall policy. A single 5-element vector was thus elicitated from each subject regarding the entire training session. This vector used in each of the three phases for automated management of information.

4.4.4 Evaluation. The evaluation of each of the 5 information choices is made according to the following equation:

$$\text{MAU}\,[I_s] = \sum_{i=1}^{5} K_i \cdot X_{is}$$

where MAU $[I_s]$ is the aggregate (multi-attribute) utility of information choice I_s, X_{is} is the level of attribute i associated with information choice I_s, (calculated using Equation 2-3) and K_i is the importance weight of attribute i. It should be noted that the program did not have access to the true state of the environment.

4.5 Experimental Procedure

4.5.1 Experimental Variables. The following experimental variables and levels were tested:

(1) Model Form - Two levels.

(a) Adaptive estimation of weights -- use of model-inferred attribute weights for prediction, evaluation, and management of communications decisions.

(b) Off-line estimation -- use of direct elicitation techniques to define attribute weights prior to the task.

(2) Communications Management - Two levels.

(a) Unaided operation -- the operator makes the information and control choices without benefit of aiding.

(b) Automated management of communications -- model based management of communications (not subject to operator override) along with recommendation of avoidance/attack option.

(3) Speed Stress - Two levels.

(a) Slow speed -- The operator has a total of 6 seconds to observe the conditions and select an information choice.

(b) Fast speed -- The operator has 4 seconds to observe the conditions and select an information choice.

The low and high speed stress levels were chosen empirically to represent two extremes of load. The low speed rate was found to provide just sufficient time for consideration of all factors. The high speed rate was designed to rush the information selection somewhat, but not to debilitate the ensuing action decision.

4.5.2 Performance Measures. The close coupling of operator and aiding system requires evaluations of (1) the overall system performance and (2) the performance of the decision model.

System Performance. The overall system performance is described using a single index, the score. The score is derived from the number and the cost of errors committed and the communications costs expended:

SCORE = {PAYOFFS} - {PENALTIES + COMMUNICATION COSTS}

The score is presented to the subject as a single index of performance, and his compensation depends to a large extent on the measure. The complexities of having speed as a second, independent measure are avoided by presenting the task at a set pace.

Decision Model Performance. The effectiveness of the decision model is evaluated in terms of behavioral prediction, operator acceptance, construct validity, and information management performance. Prediction refers to the ability of the model to predict operator behavior in both the information and action decisions. Outputs of the adaptive and off-line estimated models were compared to actual operator choices during the unaided sessions. Validity tests are made by comparing model parameters estimated by the adaptive and off-line techniques.

Multivariate analysis of variance was used to analyze the distribution of information choices and the vectors of importance weights K_i. The dependent variables in these cases are (1) the frequency with which each information type is chosen, and (2) the vectors of K_i by subject and phase.

4.5.3 Subjects and Procedure. The twelve subjects participating in the study were recruited from nearby universities and military reserve units. They represented the type of personnel who might interface with computer-aided information systems. The subjects ages ranged from 21 to 39. All had two or more years of college experience. Six were male and six were female. Six subjects had experience with computer systems and three had flying experience. The twelve subjects were assigned randomly to the six groups.

Each subject underwent two hours of orientation and practice prior to the experimental sessions. The practice concluded with a slow speed manual session, during which both adaptive estimation and off-line elicitation of attribute weights were performed. The experimental sessions consisted of three complete sequences of the cruise, surveillance, and aggression phases, 90 decisions in all. A session lasted approximately 35 minutes. Each subject experienced all six combinations of conditions in a repeated measures design (Figure 4-4). The subjects were paid $5.00 per hour and were given a bonus of up to $5.00 per hour contingent on performance.

	LOW SPEED STRESS			HIGH SPEED STRESS		
	MANUAL	AUTO ADAPTIVE	AUTO DIRECT ELICITATION	MANUAL	AUTO ADAPTIVE	AUTO DIRECT ELICITATION
GROUP 1	1	6	4	5	3	2
2	2	3	5	4	6	1
3	3	5	1	2	4	6
4	4	2	6	3	1	5
5	5	1	2	6	2	4
6	6	4	2	1	5	3

NUMBERS DENOTE SEQUENCE OF
PRESENTION OF CONDITIONS

FIGURE 4-4: EXPERIMENTAL DESIGN

5. EXPERIMENTAL RESULTS AND DISCUSSION

5.1 General Observations

The choices of information acquisition and action selection in the simulation were found to be sufficiently varied and difficult to provide a good test of model-based information management. A wide variety of behaviors were observed and modeled. The task simulation was also sufficiently demanding to maintain a high level of subject interest. The subjects learned the task procedured readily and by the end of the training session, could effectively handle the task requirements in both slow and high speed conditions.

5.2 Task Performance

Figure 5-1 shows the performance score (the payoffs less damages and costs) attained under each of the three forms of information management - manual, automated/direct elicitation, and automated/adaptive estimation. The Figure also shows the performance scores under the two levels of speed stress.

The upper portion of Figure 5-1, dealing with the low speed conditions, shows a minor (27%) advantage for automated management with adaptive estimation (Auto A) over the other two forms of information management (manual and Auto D). The lower portion of the figure shows a significantly increased aiding in the higher speed condition. Auto A then shows a 60% increase in performance over manual selection, and Auto D shows a 29% improvement over manual (all differences significant at $P<.05$, Duncan Multiple Range Test). Much of the improvement in aiding appears to be due to the significant decrease in manual performance as the speed stress increases. The automated selection performance appears to remain constant under the two levels of speed stress.

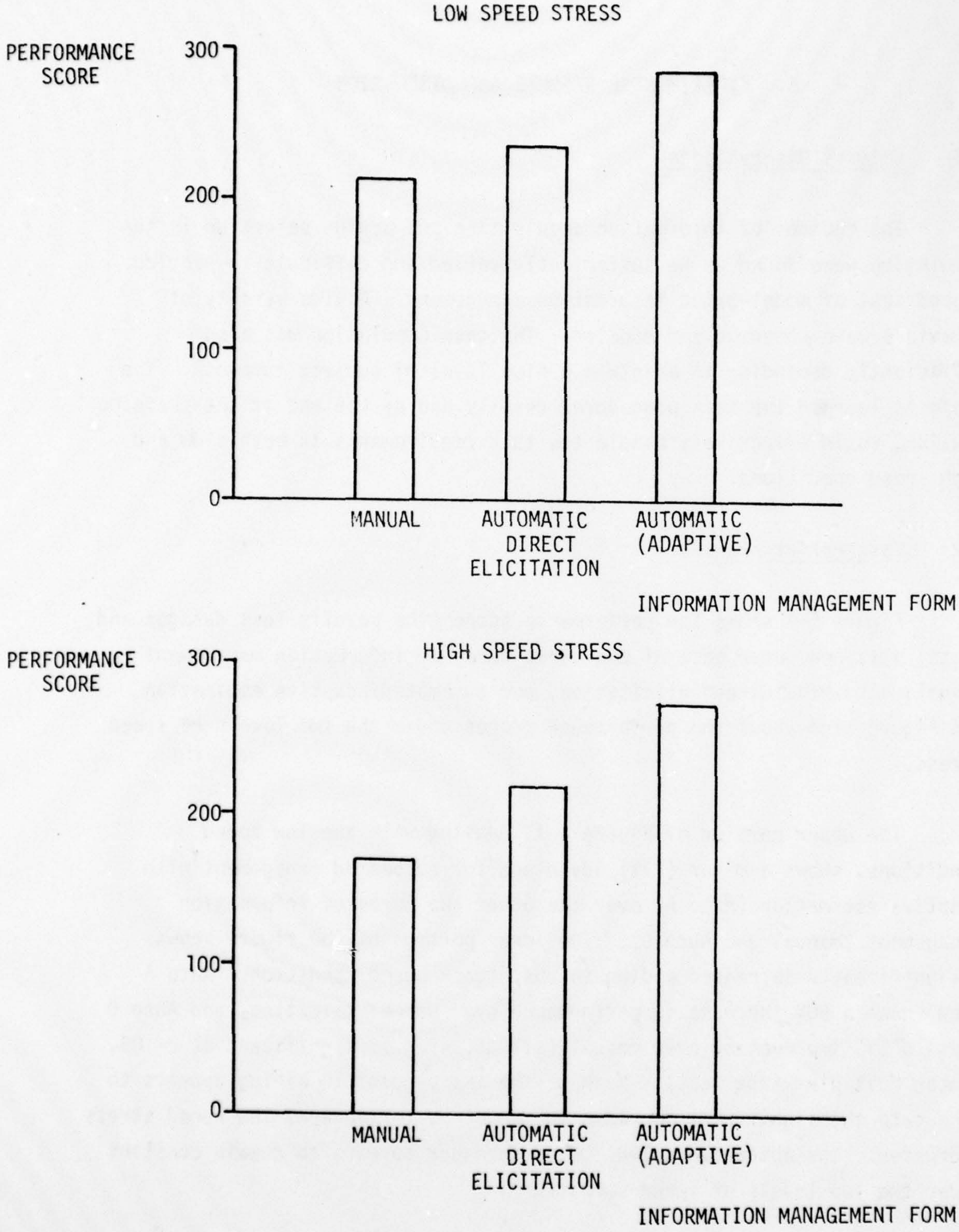

FIGURE 5-1: THE RELATIONSHIP BETWEEN INFORMATION SELECTION MODE AND PERFORMANCE SCORE FOR: (A) LOW SPEED STRESS, AND (B) HIGH SPEED STRESS

Score Components. The improvements in performance with aiding were found to be traceable to differences in both the costs expended and the payoffs attained. Subjects in the automated selection conditions (Auto A and Auto D) incurred significantly greater information acquisition costs than subjects using manual selection ($F(2,12)=10.73$, $P<.01$). Automated selection also resulted in significantly greater payoffs ($F(2,12)=13.2$, $P<.01$) compared to manual. The increase in payoffs was roughly double the increase in costs expanded, resulting in the net performance increase observed in the aided conditions.

The quality of the Auto A performance was found to depend on the performance on the training session. This is not surprising, since the Auto A selection policy is based on the training session behavior. A correlation of .62 ($P<.05$) was observed between training and Auto A scores. The correlation between training and Auto D scores did not reach significance.

Subjective Responses. The brief questionnaires administered after each session provided some support for the experimental findings. For example, ten of the twelve subjects expressed a preference for manual information selection in the low speed stress conditions. In the high speed stress conditions, nine of the twelve preferred automated selection ($P<.05$, McNemar test for significance of changes). The subject's ratings of their performance in the high speed stress conditions also followed the findings. Performance under the aided conditions was seen as significantly higher than under the manual conditions ($P<.01$, Wilcoxin matched-pairs signed-ranks test). None of the responses regarding comfort or perceived task difficulty reached significance.

5.3 Information Seeking Behavior

It should be noted that while certain trends will be apparent from the analysis of sources used, it is not possible to determine the optimal policy of source utilization for each subject. Each operator has different control capabilities using the various sources and different responses to the time delays encountered. Global rather than individualized analysis of behavior and performance will be attempted here.

Each of three information selection modes - manual, Auto A and Auto D - exhibited a different distribution of choices among the five information options. Figure 5-2 shows in histogram from these choice distributions. The upper histogram shows the almost uniform use of the five information sources with manual selection. This uniform usage may have served to overemphasize some sub-optimal sources. The Auto A selection, shown in the middle histogram, exhibited a more peaked distribution of choices, concentrating on the biological, location, and full information choices (see section 4.3 for a description of these choices). The Auto D selection, shown in the lower histogram, was intermediate in diversity among the sources.

Within the Auto A selection, some further analysis is possible. The average policies of the three highest scoring subjects are compared with the average policies of the three lowest scoring subjects in Figure 5-3. While the profiles of the two groups are quite similar, the high scoring group (the triangles in the Figure) appeared to place a greater emphasis on cost (A_1) and aggressive gain (A_5) than did the low scoring group.

At the phase-by-phase level, a MANOVA performed on the adaptively estimated attribute vectors revealed significant differences in policy between the cruise and surveillance phases (multivariate $F(5,7)=6.9$, $P<.02$) and between the surveillance and aggression phases (multivariate $F(5,7)=16.4$, $P<.01$). Between cruise and surveillance phases, univariate tests show the delay weight (k_2) to decrease ($F(1,11)=28.3$, $P<.01$) and the

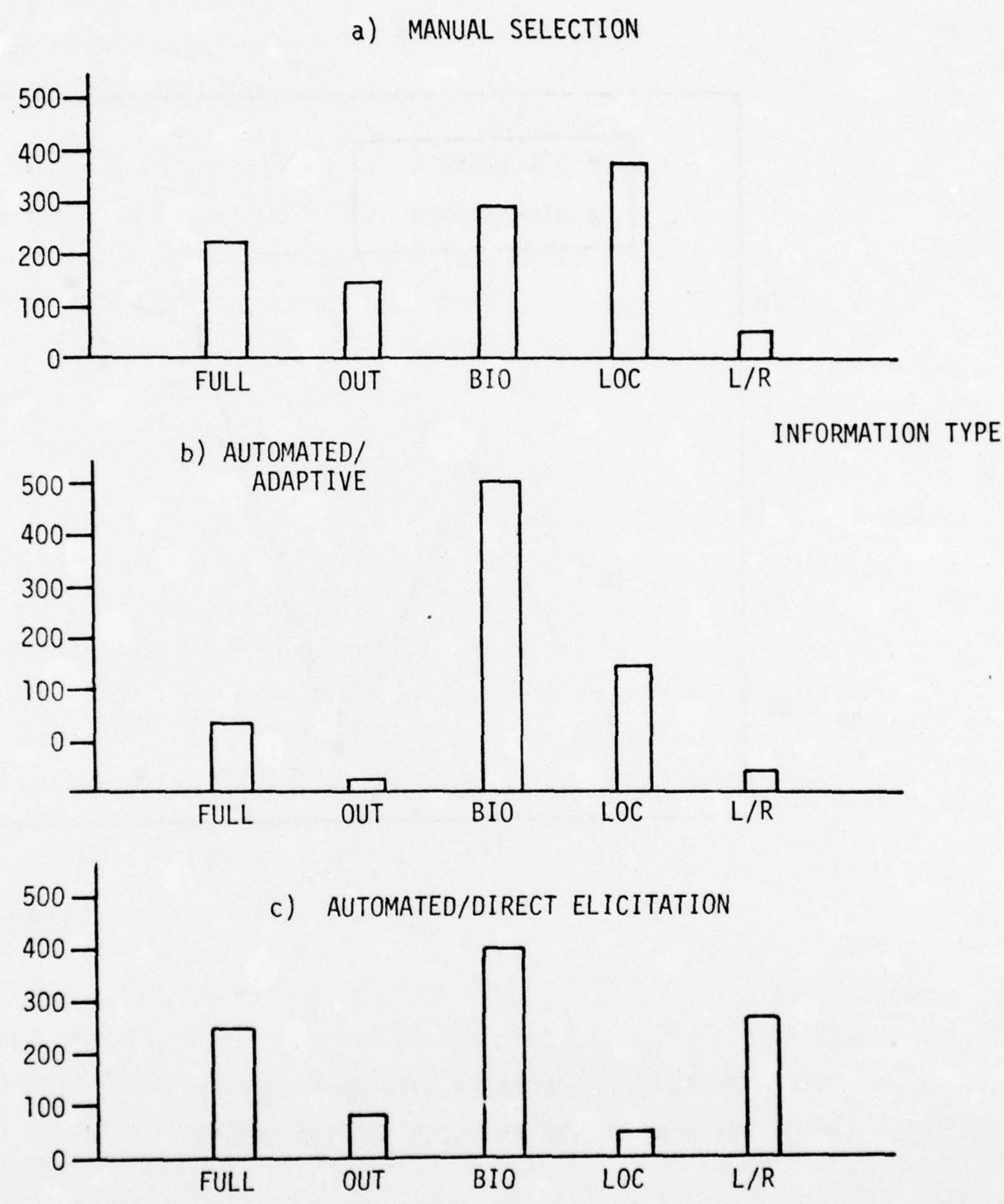

FIGURE 5-2: INFORMATION CHOICE DISTRIBUTIONS
FOR THE THREE INFORMATION SELECTION FORMS

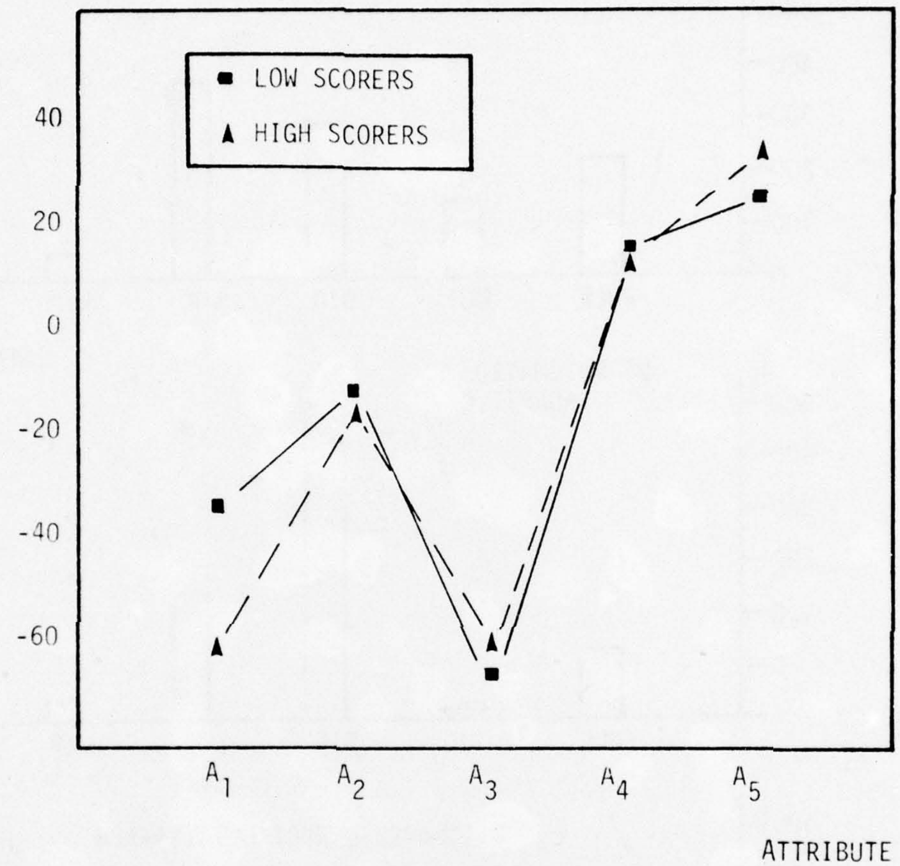

FIGURE 5-3: AVERAGED ATTRIBUTE PROFILES
FOR LOW SCORING AND HIGH SCORING GROUPS

detection weight (k_3) to increase ($F(1,11)=9.0$, $P<.02$). Between surveillance and aggression phases, univariate tests showed the delay weight (k_3) to decrease ($F(1,11)=10.7$, $P<.01$), and the aggression weight (k_5) to decrease ($F(1,11=21.9$, $P<.01$). No significant changes in the cost weight (k_1) were observed.

The presence of distinct policies for each phase may explain much of the performance advantage of the Auto A selection over the Auto D selection. As noted earlier, the off-line procedure for direct elicitation resulted in only a single overall vector for each subject instead of the phase-specific vectors obtained by the adaptive technique.

5.4 Information Value Analysis

It was brought out in section 3.4 that the value of an information source could be calculated from the operator's policy weights and the attribute levels encountered. The information sources in the task simulation have overlapping function, indicating use of the marginal contribution (equation 3-6) for evaluation. The marginal contribution is the incremental value of a source over the next most valued source. A source thus makes a contribution only when it is the highest valued of the set. As a corollary, an information source provides zero value if it is never chosen. The marginal contributions are summed over all decisions in the mission to arrive at an overall value of the information source.

A test of the usefulness of this measure is the correlation between the aggregate information value of each source and the score actually obtained using that source. The correlation across each of the three phases (15 scores in all) was .94 ($P<.01$). The correlation did not reach significance for the Auto D estimation.

By way of comparison, the frequency of use of each source in the manual mode correlated .61 ($P<.05$) with the scores obtained by that source. The correlation improved to .71 ($P<.05$) when the marginal information values were correlated with the manual scores by source. This indicates that the derived information value estimate may be more useful as a design and evaluation tool than the observed frequency of use of an information source.

6. CONCLUSIONS AND RECOMMENDATIONS

6.1 Automated Information Management

The experimental study demonstrates some of the potential of on-line, adaptive techniques for: (1) automating information selection and (2) evaluating alternative information configurations in advanced aircraft operations. In the advanced aircraft situation, the pilot is repeatedly required to make complex, subjective decisions regarding information options. Multi-attribute modesl using either pattern recognition techniques or direct elicitation methods for estimation were seen to be useful for capturing, analyzing, and automating the operator's information seeking policy.

The degree of aiding provided by the automated information selection was found to depend on the quality of the training behavior and on the degree of speed stress in the task. Not surprisingly, automated information management was most effective when it was based on parameters estimated from high performance manual runs. Also, the improvement over manual information selection was greatest in situations of high speed stress. In support of this, subjects expressed a much greater perference for automated information management in the high speed stress situations.

Overall, automated information management using the off-line direct elicitation technique was not found to be quite as effective as the adaptive technique. This may have been due to the ability to elicit only a single vector of weights for all mission phases. It is possible that other methods of direct elicitation - paired comparisons, indifference curves, probability wagers, etc. - may be sensitive enough to differentiate between sub-task policies, albeit at longer elicitation time and difficulty. The elicitation technique used was not offered as the optimal method, but merely illustrative of the procedures available. It is anticipated that in those situations where few decisions are available for training, or the decisions are too complex for effective choice, the off-line procedures would be preferred.

Increased aiding with the adaptive technique is also possible. The probability estimation programs and attribute weights were both "frozen" during the experimental sessions. Dynamic estimation of outcome probabilities specific to each subject should improve the accuracy of the attribute level estimates and, in turn, result in more effective information selection. Similarly, allowing the attribute weights to adjust dynamically with the task demands should improve performance.

6.2 Information Value Estimation

The multi-attribute model was found to provide a useful framework for ascertaining the value or contribution of each information source. The marginal contribution estimated for each information source in the experimental study proved to be a good estimator of the actual score attributable to that source. This information value was specific to the individual decision maker and the sequence of task circumstances encountered.

The Adaptive model employed in this study was constrained to an application of moderate complexity - multiple criteria, probabilistic consequences, and time-varying behavior. Extension of the domain of application to more complex circumstances - limited resources, continued sampling of information, and multiple tasks - is scheduled for the coming year. Accomplishment of these extensions should allow application to a variety of operational systems.

7. REFERENCES

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