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MODELING HUMAN DECISION PROCESSES IN COMMAND AND CONTROL

Contract Number N00014-81-C-0740

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IN COMMAND AND CONTROL

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The primary goal of this ongoing project is to model human behavior in specific situations and, in particular, to model high-level decisionmaking for antisubmarine warfare commanders. To abet this modeling effort the SHOR paradigm is presented as a structure for analyzing human cognitive decisionmaking. SHOR describes decisionmaking as a cascading of four activities, they are: information processing, hypothesis generation and evaluation, option generation and evaluation, and decision execution. → cont

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SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered) cont The commander's decisionmaking process is cast into the SHOR framework. A Bayesian (optimal) mathematical model of the decisionmaker's hypothesis evaluation procedure is developed. The inputs to the model are the hypotheses and sensor data, and its outputs are the posterior probabilities of the hypotheses' being true and their respective states of nature. It is assumed that these outputs are sufficient for the commander to perform the option generation and evaluation activities.

A brief example of how the posterior probabilities of the hypotheses evolve in the light of new data and implications of the model are presented.

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SECTION 1

INTRODUCTION

The goal of this ongoing project is to develop and to validate a mathematical model of a Naval commander's decisionmaking process. This process is comprised of planning, organizing, and executing a given mission [1].*

A model of a commander serves two purposes. They are: (1) to diagnose, or to identify, the commander's cognitive limitations that render him boundedly rational, and accordingly suggest decision aids or support systems that will enhance his performance, and (2) to appraise the effectiveness of such improvements in the command and control (C^2) network, in which the commander is but one element.

1.1 METHODOLOGICAL FRAMEWORK

Models of human decisionmaking are often classified into three categories: normative models, descriptive models and normative-descriptive models. Normative models, by definition, prescribe how decisions should be made when the decisionmaker's objectives are explicit [2;3]. Models that mimic human decisionmaking behavior, in a non-humanoid way, are descriptive. These models are used when decisions are repeatable, and are often referred to as "bootstrapping" models [4]. Normative-descriptive models assume that the decisionmaker strives to be optimal, but is constrained by cognitive and, to

*References are indicated by numbers in brackets, and appear at the end of the report.

a lesser extent, neuromotor limitations. The normative-descriptive approach is employed herein.

1.2 HUMAN DECISIONMAKING

A paradigm for the process of human decisionmaking has been conceptualized by Wohl [1]. Wohl generically describes the decisionmaking process as a cascading of four activities. They are:

1. Information processing.
2. Hypothesis generation and evaluation.
3. Option generation and evaluation.
4. Execution.

He has coined this paradigm SHOR (stimulus-hypothesis-option-response), since it is an extension of the stimulus-response (S-R) paradigm of classical behavioral psychology [5]. SHOR is a framework for structuring decision problems. It is not an analytical model. When referring to a SHOR model, what is implied is a model that has been devised within the SHOR framework.

In this report, the commander's decisionmaking process is cast in the SHOR framework, and a model for hypothesis evaluation is proposed. The hypothesis evaluation technique is normative in construct. It closely parallels the control and estimation theoretic [6] approach to hypothesis testing. The sufficient information for option generation and evaluation is suggested.

1.3 COMMAND AND CONTROL

Throughout this report, reference is made to the C^2 process and the command, control, and communication (C^3) system. Various groups and individuals have imbued these terms with somewhat different meanings. Thus, it behooves us to define what we are referring to by the C^2 process and the C^3 system.

The C^2 process is a coordinated set of information gathering and decisionmaking activities, carried out with the objective of effective force application, i.e., the best utilization of platforms and weapons in the battle environment. The C^2 process is supported by the C^3 system. The C^3 system is a collection of sensor, information processing, and communication subsystems that allows the C^2 organization, which is comprised of military personnel operating within a hierarchical authority structure, to receive information from and transmit information about the battle environment, facilitating information interchange between the members of the C^2 organization.

The C^2 process thus involves a collection of human activities, organized to accomplish certain goals. There exist no precise, standard techniques for describing the C^2 process, much less for analyzing or designing it. Part of the difficulty in describing this process is because it is a dynamic process, carried out by a team of people, who may be distributed over a large geographic region and who are forced to operate under conditions of both information and outcome uncertainty in achieving their individual goals and those of the overall C^2 organization.

1.4 OUTLINE OF THE REPORT

Section 2 reviews several theories of human response and introduces the SHOR paradigm. Section 3 describes a mathematical model of the decisionmaker's hypothesis evaluation procedure cast in the normative framework. A discussion of the effort to date and recommendations for next year's research comprise Section 4.

SECTION 2

HUMAN RESPONSE MODELING

The major task for this project is to model human behavior in specific situations and, in particular, to model high-level decisionmaking for anti-submarine warfare commanders (ASWCs). It is generally agreed that a model consists of a set of assumptions, an organizational framework, and a set of rules for manipulating the details of the model. Models of human behavior are usually validated using human performance data obtained from laboratory simulations and/or field experiments [7;8;9].

Several approaches can be employed for modeling human behavior as depicted in Fig. 2-1. These approaches can range from simple descriptive models to models depicting optimal human behavior. Most of these models can be categorized into three classes as discussed below.

2.1 DESCRIPTIVE MODELS

The descriptive models of human response attempt to accurately depict observed human behavior. As such, these models require an oftentimes large data base in order to explore relationships and deduce trends. By construct, descriptive models in the engineering domain are _a posteriori_ in nature, and often with little or no underlying theoretical foundation. The model results are generally task specific, since they focus only on the data associated within a specific context. The net result is a model with extremely limited

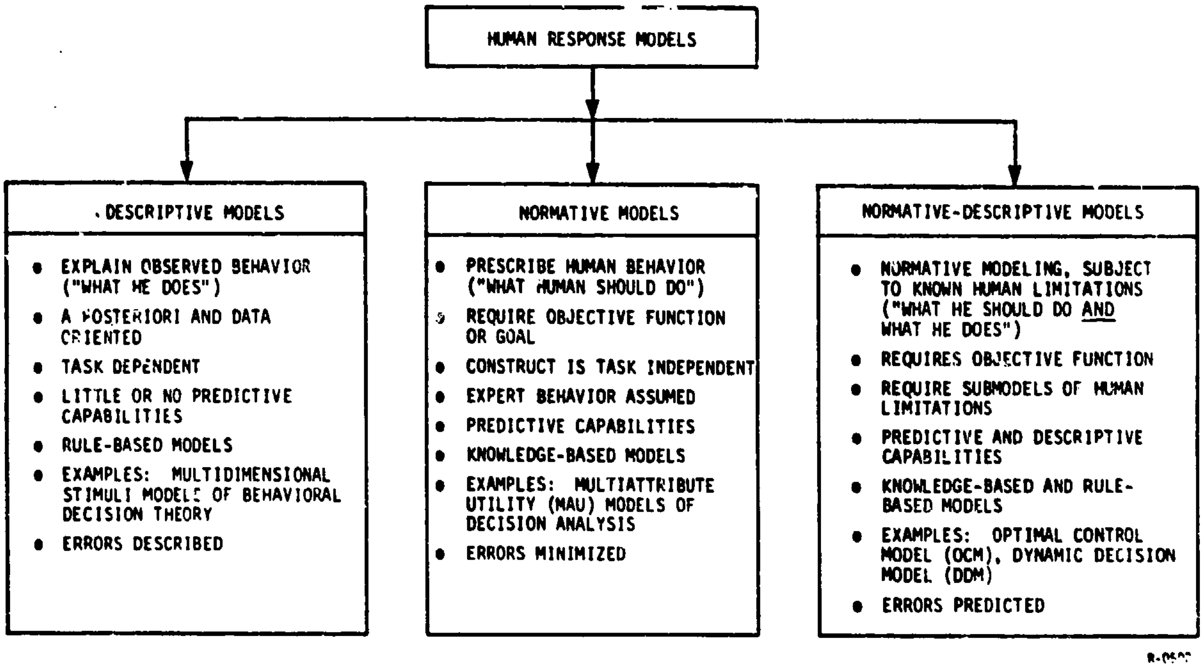

Figure 2-1. Models of Human Behavior

predictive capability in describing human response or performance in a different environment. Human response models that are rooted in psychology, biology, and ergonomics are often descriptive.

An example of a descriptive model is the error rate of a human in a target identification and classification task (e.g., attack or reconnaisance aircraft, friendly or enemy). The error rate, e.g., 2 errors/1000 targets, as measured in the performance of the classification task, is not linked to any underlying theoretical reasoning. Also, it is doubtful whether this number has any utility if one wishes to know the error rate in a different task environment, or when the operator is provided with better information.

Most descriptive models are regressive. In this framework, a human's control or decision (or dependent) variable, d_i, is written as a linear combination of the pertinent system variables or attributes (i.e., the independent variables), x_j,

$$d_i = \sum_j c_{ij}x_j \quad .$$

The coefficients c_{ij}, which are the slopes of the regression lines, are derived by regression analysis using data for the x_j and d_i. This equation forms the basis for the early models of manual control and for many other decision models. However, a drawback of these models is that the resulting c_{ij} have no intrinsic meaning; if the task is changed, a new set of data must be collected and a new set of c_{ij}'s computed. Clearly, such a model is not predictive.

2.2 NORMATIVE MODELS

This class of models is predicated on the assumption that human behavior is optimal in some well-defined manner. For example, in a decision context one can assume that the human will compete against nature (or an adversary) to maximize his expected gain, or utility, over a given time horizon. In another view, one can assume that the human's response is specified by a regressive equation similar in form to that presented above but then the human tries to maximize reward - or any rational criterion - by optimizing the selection of the coefficients c_{ij}. Decisionmaking models developed through the more mathematically oriented disciplines, such as the control, stochastic estimation, information, probability, and decision theories are typically normative.

The key ingredient for developing a normative model is the specification of an objective function or goal that is assumed to be extremized by the human. Once specified, tools of optimization theory* can be applied to solve for an optimal policy or decision rule. Thus, the approach is capable of generating predictions of optimal human response without the need for a priori data. Furthermore, the optimization approach is not limited to any type of task so long as a task objective can be specified.

This class of models prescribes what a human should do. However, experience with such models has shown that the model results tend to be overly optimistic, i.e., model performance exceeds human performance; human performance is nonoptimal. This is exemplified by the findings of Tversky and Kahneman [10], Lopes [11], and Einhorn and Hogarth [12], all of which indicate that people do not adjust their probability estimates in strict accordance with Bayes theorem. Attempts to bring model results into agreement with data usually focus on generating a nonoptimal decision rule for the human, or on modifying his objective function. Thus, concepts such as discounting future rewards, optimization over a limited future horizon, and substitution of utilities for task values have been introduced as modifications to otherwise purely normative models.

2.3 NORMATIVE-DESCRIPTIVE MODELS

This class of models is normative in construct, but with the assumption that the nonoptimality of the decisionmaker arises from his own inherent limitations; for example, delays in identifying and classifying targets, aggregating and processing information, randomness, limited processing "bandwidth," short-term memory (STM) limitations, and limited combinatorial capability.

*For example, dynamic programming, maximum principle, calculus of variations, least squares, etc.

Thus, the normative-descriptive models are couched on the hypothesis that the human tries to respond optimally, subject to these limitations. This normative construct requires the specification of an objective function or goal, as in the normative case, but optimization is now constrained.

The descriptive features of the models are those associated with the human's limitations. Thus, the model does not attempt to explain why or how certain limitations arise, but rather includes their effects as constraints. For example, numerous experiments in the psychological literature indicate a maximum storage capacity for STM of seven (plus or minus two) items [13].

Isolating and mathematically representing the important human limitations is the essence of the descriptive portion of the normative-descriptive class of models. Clearly, human response data are necessary to accomplish this task. In addition, we must ensure that the limitations are not task dependent, but are indigenous to the human among tasks, e.g., time-delay and randomness.* Fortunately, with the aid of human response data from the experimental psychology literature, it has been possible to isolate and quantify many of the principal limitations. Thus, the normative-descriptive models are truly interdisciplinary in nature. They are also capable of representing individual differences.

The normative-descriptive models have the ability to generate predictions of human response and performance once the objective function and limitations are specified. The fact that this class of models lies between the purely normative ones and the descriptive ones implies that this approach attempts

*Thus, data from simple, independent experiments that focus on identifying the limitations can be used as a descriptive constraint in more complex scenarios.

to equate what a human does with what he should do. Employing this principle of bounded rationality, the normative-descriptive models have generally met with excellent success in application. In manual control situations, the normative-descriptive approach led to the development of the optimal control model (OCM) of human response [7;8]. In complex decisionmaking contexts such as C^3 systems, however, where the cognitive skills of the operator predominate over the motor skills, there are virtually no normative-descriptive models. Indeed, there is not even a consensus on modeling, and only a few descriptive studies exist in process control situations [14]. One beacon, however, is the application of a normative-descriptive construct to multitask selection or sequencing where a variety of tasks compete for the decisionmaker's attention. The dynamic decision model (DDM), developed for this situation, captures the interplay among human estimates of time required, time available, and expected reward, while including submodels for various human limitations [9]. There has, however, been a paucity of research aimed at extending the normative-descriptive modeling approach to more complex decisionmaking tasks such as those of C^2. An example does exist within the electrical power domain [15], in which the decisionmaking behavior of power grid dispatchers in emergency situations has been successfully modeled in line with normative-descriptive constructs.

2.4 MODES OF HUMAN BEHAVIOR

Another issue that must be addressed when modeling human decisionmaking is the classification and representation of the different modes of behavior. Rasmussen [16] has suggested a classification that delineates three types of behavior: skill based, rule based, and knowledge based.

Skill-based behavior refers to actions with a strong habitual, inveterate flavor, such as manual control or simple information processing. Not much conscious attention need be directed toward such behaviors. Behavior that is governed by procedures or doctrine is termed rule based. Knowledge-based behavior requires individuals to extract the appropriate information from their knowledge base and construct or deduce the appropriate rules or skills to employ. It is assumed that decisionmaking, hypothesis generation and hypothesis testing involve knowledge-based behavior.

The importance of appropriately identifying what class or classes of behavior are involved bears directly on how that behavior is to be modeled. Skill-based behavior might call for neurophysiological equations, while look-up tables or production systems can be used to represent rule-based behavior. Knowledge-based behavior requires a different and more abstract tack, such as knowledge of objective functions, cost functions, or goals, so that such behavior can be encoded.

2.5 THE SHOR PARADIGM

The SHOR paradigm [1] was developed to provide a framework for decision task description in C^2. A task will often have certain well-defined properties or structures and it is the purpose of SHOR to provide a useful mechanism to describe these salient task features.

In essence, the SHOR paradigm is derived from the stimulus-response (S-R) principle [5] of classic behavioral psychology. The basic elements of the SHOR paradigm are shown in Table 2-1. As depicted in the table, raw data are sensed and processed by the perception processor, i.e., in the S component of SHOR. Processed data are then operated on by the H component of the SHOR paradigm. This operation addresses the question: What is the situation or state of the system? Hypotheses are generated and evaluated to formulate or to describe the state of the system. Once hypotheses are formulated, the O or option generation and evaluation operation addresses the question: What if this or that is done? Options are considered and evaluated in the light of the current hypotheses about the situation and the desired mission objectives. Lastly, an action or response, R, is organized and executed in line with the option selected, and in turn creates an observable effect on the states of nature.

TABLE 2-1. SHOR PARADIGM IN TERMS OF TASK ELEMENTS

	S	H	O	R
	STIMULUS	HYPOTHESIS	OPTIONS	RESPONSE
TASK	PROCESS DATA	MAP DATA INTO INFORMATION	EVALUATE ADMISSIBLE ACTIONS	EXECUTE ACTIONS
INPUT	ENVIRONMENTAL DATA	SENSORY DATA	HYPOTHESES ABOUT STATE OF NATURE	DECISIONS THAT AFFECT STATES
OUTPUT	SENSORY DATA	HYPOTHESES ABOUT STATE OF NATURE	DECISIONS THAT AFFECT STATES	RESPONSES

2.6 ELABORATION OF THE SHOR PARADIGM

It is assumed that the decisionmaker is continually processing and analyzing information and, when necessary, executing responses that have some specific impact on the real world. Thus, to observe a decisionmaker is to observe an ongoing process, and when using SHOR to describe this process it must be viewed as dynamic.

It is assumed that the decisionmaker's actions or responses affect the real world through a set of controlled variables. The effect of these responses, as well as those of other uncontrolled variables (e.g., enemy action and weather), are detectable by surveillance and intelligence sensors, and can become input data or stimuli for the perception processor. The perception processor utilizes data-driven and/or concept-driven processes to search the incoming data for patterns to recognize and classify.

The hypothesis or set of hypotheses under consideration is the result of interaction in the perception processor between the incoming data and the human's internal representation or mental model of the total system with which he is dealing. The more expert the individual, the sharper and richer the mental model. In any case, the resulting hypothesis provides the basis for comparison of the incoming data with predictions derived from the hypothesis. Given a set of alternative hypotheses, incoming data may serve to increase the decisionmaker's subjective confidence in one hypothesis over the others. Alternatively, the data may not support <u>any</u> of the hypotheses. Note that it is this condition where no hypotheses are supported by available data that leads to an alteration of one's mental model. Likewise a single hypothesis may or may not receive support. If no hypothesis is supported by the data, one must then reconsider the validity of both data and hypothesis and perhaps modify the hypothesis accordingly. The hypothesis with the greatest subjective confidence or perceived likelihood of being correct will be used to help generate response options and, ultimately to help select a response.

2.6.1 Functions and Characteristics of the Perception Processor

At the stimulus or sensory end of the perception processor we are dealing more with data processing than information processing, although the two processes can never be completely dissociated. If we consider the outside world in purely physical terms, it can be described as a flux of energy that exists in different forms and at different levels [17]. Here, the problem is one of detection. Human sense organs are responsive to only a tiny portion of the electromagnetic, mechanical, and chemical flux. Early psychophysical concepts of fixed sensory thresholds have given way to modern signal detection theory, which describes variations in detection probability in terms of a receiver operating characteristic (ROC) curve. The ROC curve depicts the likelihood of a subject's guessing that there is a signal present when in fact there is one, and the likelihood of his guessing that a signal is present when in fact there is none. Signal strength relative to noise background certainly has an important impact on the ROC curve as a whole, but variables such as cost, utility, expectancy, attitude, and the like are equally important in that they serve to bias the operating point on the ROC curve. In fact, it has been argued that in most real situations detection results are determined more as a function of subjective variables (e.g., perceived costs and attitudes) than by sensory acuity. This also implies that appropriate training, specific monitoring procedures, and well-designed displays can mitigate the negative effect that certain psychological variables can have on detection.

DATA-DRIVEN VERSUS CONCEPT-DRIVEN PROCESSING

Operations that are set in motion by arriving data are referred to as data driven. Lindsay and Norman [18] describe the data-driven process as follows: the onset of processing is initiated by incoming data; each of several stages of analysis performs its operation of receiving input (data) and doing something with it; and the outputs of each stage are the inputs that drive the next stage. This process proceeds in a smooth, logical progression culminating in the recognition of the item. Nothing happens within a data-driven system until data are input at one end. This is contrasted with a concept-driven process, which begins with a conceptualization of what might be present (i.e., a hypothesis) and then looks for confirming evidence, influencing the processing mechanism to search for the expected results [18]. A perceptual process is concept-driven whenever knowledge of the possible interpretation or conceptualization of something helps in perceiving that thing. Finally, it must be emphasized that neither process alone is sufficient to explain or carry out the perceptual processing of data. Therefore, in this study both are assumed to be occurring simultaneously.

CLASSIFICATION AND RECOGNITION

Initial perceptual processing of the sensory data involves both attention allocation and pattern recognition. First, it is necessary to sort out relevant data from the myriad of sensory inputs. Then the problem becomes one of pattern recognition. Immediately we are faced with an apparent paradox: it appears that we must understand the meaning of data before we can analyze its content properly; but how can we understand the meaning of data before the analysis of its content has occurred [18]? If we assume that the human brain is capable of simultaneous analysis at several levels*, a resolution of the paradox is possible. In particular, we assume that perception is both concept-driven and data-driven, that these two forms of processing interact with each other, and that their combined power is capable of analyzing data that neither process can deal with alone.

One of the simplest schemes for classifying and recognizing patterns, and a prime example of a data-driven process, is template matching. For each pattern to be recognized there must be some preexisting template (representation). To accomplish recognition, the incoming data pattern is matched against the preexisting template. Template matching is quite straightforward; since incoming data patterns are assumed to be matched against all of the possible templates simultaneously, the cumbersome procedure of trying out a succession of templates one at a time to find the best fit is eliminated. Unfortunately, simple template matching lacks the flexibility to account for human pattern recognition, since if the incoming data varies even slightly (e.g., in size or orientation) from the template, the procedure will fail. The introduction of fuzzy templates or of preprocessing of the data before a match is attempted can often improve matching.

An alternate view is that specific templates are not employed. Rather, specific feature detectors are used, and there is good evidence that such detectors not only exist but map directly onto neurological structures and organizations within the brain. According to this theory, a succession of feature processors work on the incoming data, with each processor performing a

*The brain's ability to simultaneously process information at different levels is supported by the work of Karl Pribram, who argues that the brain is holographic in nature when considering storage and processing [19].

different function. The outcome is a decision on what the most likely pattern is that conforms to the data. If conceptual processing (i.e., some knowledge or expectation of what the data must be beyond what is actually present in the data) is added to such feature processing, the likelihood of successful interpretation is further increased. This added information might come from the context of the sensory data, where the overall environment in which experiences are embedded represents what is meant by context. As Lindsay and Norman [18] have pointed out, the ability to use context makes the human perceptual system far superior and more flexible than either feature detection or template matching alone. The combined effects of data-driven and concept-driven processes thus provide a basis upon which higher cognitive processes can act.

Note that while descriptive paradigms such as those mentioned above exist, there are at present no mathematical models of these processes and few good theories on which to base such models.

2.6.2 The Human Internal Model

As a human becomes well-trained in a specific man-machine system task and context, he develops an internal characterization of the dynamical response and behavior of the system with which he interacts [14]. This mental model, which is refined through the processes of learning and experience, is one of the key discriminators between rule-based human response and knowledge-based response [16]. As such, inferring the human's internal model is a necessary precursor to the development of normative and normative-descriptive models.

The concept of a mental model has long been recognized in the psychological literature (e.g., Tolman's "cognitive maps" or Lewin's "life-space") [20;21], but only of late has the concept begun to evolve into a mathematical construct, sufficiently well understood for inclusion within an overall human-system model [9]. An internal or mental model may be thought to consist of three basic ingredients: (1) a description of the variables (states) of importance, including external inputs and disturbances (independent variables) and outputs (dependent variables); (2) the assumed causal and/or correlational relationships that exist among the variables; and (3) values for the coefficients (relative importance of terms) in the equations that define the relationships. In any given context the process of eliciting or inferring a human's internal model of system response is extremely difficult. In highly complex decisionmaking contexts, the number of system variables becomes too large, so that aggregation or chunking within the internal model is likely. In addition, static relationships among variables are likely to dominate in the internal model.

An internal model serves three primary functions in the broader human-system modeling context: hypothesis generation, data interpolation, and outcome extrapolation. First, the relationships among variables in the internal model can be used in the process of transforming data into information by means of filtering, estimation, correlation, and discarding of input stimuli. It involves data validation, which in turn affects internal model validation. The second function of the mental model involves its use for prediction or extrapolation, i.e., in directing the search for confirming or disconfirming data. This is the process of determining what additional data should be perceivable, given that the hypothesis based on the mental model is the true one. This requires a rich and robust mental model, an estimate of the present state, and an estimate of system inputs/disturbances over a prediction horizon. Herein lies one of the two main sources of uncertainty in decisionmaking:

- Information input uncertainty. Errors in estimating the present state due to imperfect internal modeling or sensory limitations in perceiving input data will affect prediction, interpolation, and evaluation accuracy.

Since the internal model is only an approximation to the actual situation or system dynamics, the effects of uncertainties will always be present. Indeed, it is often possible for an internal model to be misled, thereby exacerbating the effects of any uncertainties. Finally, the third function of the mental model involves its use in outcome extrapolation and option analysis. The internal construct that a Naval warfare commander holds of the process of a mission's unfolding not only serves to correlate the various measurements he obtains, but also provides him with a means to assess the effects of an action. Herein lies the second major source of uncertainty in decisionmaking:

- Consequence-of-action uncertainty. Errors in the internal model relations, combined with large uncertainty as to the decisions/actions of nature or an adversary, will cause the future evolution of system response to differ from that predicted by the internal model.

Determination of a suitable mental construct and representation by a set of verbal rules or mathematical equations for purposes of analysis is a necessary, albeit difficult, aspect of describing an individual's cognitive activities in a given situation. On the one hand, the internal model must capture the fundamental static and dynamic relationships inherent in the military situation or engagement. On the other hand, the model must be sufficiently simplified and or aggregated so as to be compatible with human cognitive limitations and constraints.

2.6.3 Hypotheses

In many ways the concept of a mental model is closely allied with that of a hypothesis. For example, one can conceive of a hypothesis as a mental-model aggregated and specified for a particular set of circumstances. This conception assumes that a subset of the variables delineated in the "general" or "full" mental model are selected for the specific situation at hand, together with the appropriate functional relationships and coefficients. Each hypothesis represents a specific conceptualization of the state of nature and hence a model of the particular situation - it is the human's attempt to assess the situation.

It is assumed that an individual can hold more than one hypothesis at a time, which implies different alternative specifics of the situation. An individual in such a situation might be heard saying: if the situation is not "A" (if "A" is not the state of the system), then it might be "B" (some other state of the system). Given human STM limitations, however, it is unlikely that an individual can seriously consider more than two or three hypotheses at any one time.

2.7 HYPOTHESIS GENERATION, MENTAL MODELS, AND MEANING

Hypothesis generation addresses the problems of how people generate a reasonable set of hypotheses and modify the set as the need arises. Hypothesis generation, including what is commonly referred to as creative thinking, involves searching memory for relationships that seem appropriate to the situation.* Well-trained individuals by definition possess a rich and

*In spite of its importance, until quite recently very little attention was devoted to the issue of hypothesis generation (see Bruner, Goodnow, and Austin [22] or Wason [23] for some laboratory experiments on concept attainment and "discover the rule" type tasks).

detailed knowledge base and mental model from which to infer possible situations causing an event. But what exactly is it that these experts are doing? Is it a creative activity (a mentalist view), or are they simply processing information (a reductionist view)? Neither view appears tenable since the former is not subject to experimental verification and the latter does not address the underlying meaning of the information being processed. In fact, whereas information theory sidesteps the issue of meaning and deals only with symbol transmission rates and errors, understanding and describing the human decisionmaking process requires the consideration and operational definition of meaning. We assert that the fundamental purpose of hypothesis generation is to extract meaning from data. This assertion gives rise to a measure of performance for the hypothesis generation subtask. Since data take on meaning in the form of hypotheses, the extraction of meaning from data can be measured in terms of hypothesis uncertainty. As we shall see, the task of hypothesis generation thus is really a task of meaning extraction and, concomitantly, uncertainty reduction.

Uncertainty in physics and in information theory is a well-defined mathematical concept, one directly associated with the variance of a stochastic process and the resultant probability of occurrence of a given outcome at a given time. While this approach is satisfactory from a mathematical standpoint, the term itself is subject to confusion and argument when attempts are made to extend its application beyond physical systems. Shannon, for example, explicitly chose to eliminate the concept of meaning from his work, defining information as negative entropy (or certainty) in terms of discrete symbols and their probabilities of occurrence, or in terms of signal-to-noise ratio [24].

This limited definition, while extremely powerful for communications system engineering purposes, is of little use in designing C^3 systems. A C^3 system's major functions, in addition to the obvious ones of (1) gathering and disseminating information, and (2) planning, organizing, and executing responses; include assisting decisionmakers in extracting meaning and in predicting outcomes.

- Meaning extraction. An issue in extracting meaning from input information appears to be how military commanders deal with hypotheses. For example, having no hypothesis about the meaning of a given input data set is tantamount to all possible hypotheses being equally likely. At the other extreme, having a large and well-structured set of hypotheses tends to overburden one in the opposite direction. Neither extreme serves to focus attention upon what new information is to be sought. Given a plethora of information and a number of hypotheses, the philosophical operationalist's view must be held: a hypothesis is useless unless its predictions can be tested. This rule will serve to reduce the set of hypotheses under consideration to a subset of testable ones. The next step is to test, and that requires that new information be sought. As a case in point, new sensor and sensor correlation equipment on Aegis ships will be able to provide simultaneous information on hundreds of targets. The critical needs will be those of: (1) blocking irrelevant information, and (2) cueing of selected sensors to obtain discriminant information on selected targets in real time. But neither can occur in the absence of hypotheses. One, or at most a very few, carefully constructed hypotheses will serve: (1) to eliminate from wasteful consideration that input information that is not relevant, and (2) to direct attenion to requisite new discriminant information to further reduce the hypothesis set. We assert that tacticians, strategists, diagnosticians, executives, and commanders are expert to the degree that they possess and effectively exercise this ability of hypothesis generation and testing.

  Wise's [25] concept of "emergent decisionmaking" implies a process of hypothesis creation, development, refinement, test, rejection, modification, and ultimate acceptance and action. As suggested by Wohl [1], the convergence of this process may give rise to the perceived "emergence" of a decision. We further assert that the rate of hypothesis convergence is an important contributor to the rate of reduction of subjective uncertainty.

- Outcome prediction. The key issue in predicting military outcomes seems to be how commanders utilize the hypotheses they construct. As noted earlier, his mental model is really a commander's aggregated model of reality. To the extent that his model is accurate and the sources of variance (e.g., data accuracy, enemy and own force behavior, and weather) are small, he can formulate hypotheses and predict outcomes associated with various action alternatives.

  While the commander's model of reality is certainly not a mathematical one, he nonetheless uses it in just the same way as a scientist does. Based on data, he constructs a hypothesis involving events, relationships, and causality. He then tests his hypothesis by using it to predict the course of events given a new set of conditions, later observing the degree of concordance of the actual versus predicted course and modifying his hypothesis accordingly. Thus we see that the hypothesis, as well as being a model of reality, can also act in a very real way as a generating function for future scenarios.

It is important to note that the number of hypotheses generated with respect to a given data set is not a useful measure in this context, contrary to Gettys et al. [26]. As noted above, too many hypotheses are as detrimental as none at all.

Thus, how human decisionmakers accomplish hypothesis generation is a critical issue. Recent work on analogical reasoning and mental models has shed some light on the process of human hypothesis generation. The analogical reasoning view of Klein [27] asserts that when faced with a problem or a decision situation we search memory for similar or analog situations; the solutions to past problems (or minor variations of them) become the current hypothesis set to be tested. A process similar to the analog process is to scan memory for a parallel situation and then to manipulate the variables that seem to have led to solutions in the past for possible applications to the present problem.

The mental model position [28;29] contends that the hypothesis set derives directly from the interaction of input information with an expert decisionmaker's mental model or internal representation of a problem situation. If a mental model can serve as a theory does in science, then hypotheses can be derived from them in a similar manner; namely from the set of elements or variables comprising the theory, the functional relationships among the elements or variables, and the constraints on the functional relationships. By extension, the same should hold for expert knowledge domains.

For highly trained expert decisionmakers (commanders), the analogical view of hypothesis generation seems an appropriate position. For example, we assume that ASWCs will be searching their knowledge base for similar or analogous situations as a basis from which to generate plausible hypotheses about the current state of nature.

SECTION 3

MATHEMATICAL REPRESENTATION OF SHOR: CONCEPTS AND PROCESSES

This section describes the mathematical details of the normative model of the human decisionmaking process as developed to date. The model is composed of well-known types of simple components, chosen for their tractability and familiarity, which, when combined, behave like a human decisionmaker. The model components were selected for their input-output behavior, and not because their internal workings resemble those of the human mind. Similarly, the model details might, at times, seem more complex or redundant than the human internal processes we associate with them. For example, we need relatively sophisticated mathematics to capture the idea of a human choosing the "best" hypothesis, or reevaluating the data in the light of a new hypothesis - actions that seem simple and natural. The complex mathematics, however, have simple parameters that we can associate with mental views of the world and human limitations.

The section is organized as follows: subsection 3.1 presents an overview of the SHOR model as developed to date. Subsection 3.2 then presents an overview of the first half of the model (dealing with hypothesis evaluation) in more detail, and subsection 3.3 describes the individual elements used for this half. Subsection 3.4 presents an example of what the model variables would be in a hypothetical ASW application, and subsection 3.5 discusses how model behavior relates to parameter selection (in particular, how errors behave with time).

3.1 SHOR OVERVIEW

The SHOR paradigm represents a sequential breakdown of human information processing. New information (stimuli) are processed and given meaning - causing one or more hypotheses to be generated and considered. These hypotheses, and the decisionmaker's estimates of their relative probabilities of being true, are used to evaluate possible actions (options) before a response is chosen. The process is shown schematically in Fig. 3-1, where the stimulus (S), hypotheses (H_i), and response (R) are process variables (functions of time) and the hypothesis and option evaluators (H,O) represent operations on these variables. The generation of hypotheses and options requires a higher level of creativity, and modeling, than their processing and evaluation, and will be treated separately in a subsequent phase of this research examining mental models as generating functions.

The overall intent of this model is to represent the human decisionmaker as a controller working in an uncertain environment with multiple hypotheses about what is going on in the battle. This process can be represented as in Fig. 3-2, where the stimuli are measurements (z) made of the real world; state estimates ($\hat{x}$) and subjective probabilities are formulated about the real world; and control actions (u) are selected to affect the real world.

The state of the system refers to the total collection of underlying variables that change with time and that are sufficient to capture the status of a system. The data refer to the much smaller collection of measurements - noisy samples of some of the state variables - that are available to the decisionmaker. The state estimates ($\hat{x}$) are his internal estimates of the true state, based on all of the data available. There is a separate state estimate for each hypothesis, since each corresponds to a different view of what is

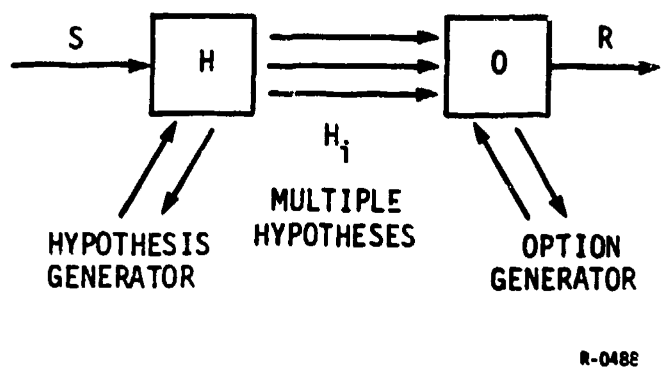

Figure 3-1. SHOR Model

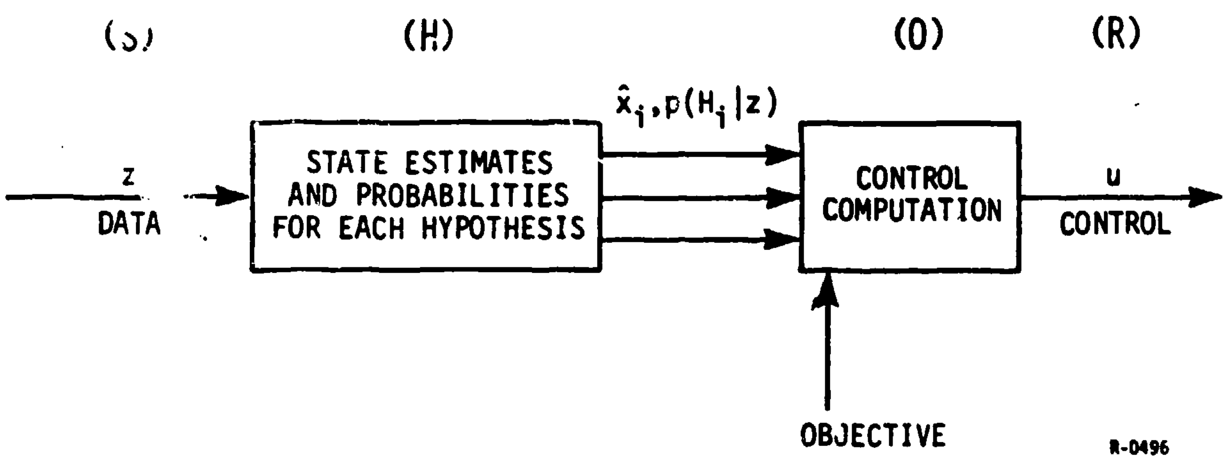

Figure 3-2. SHOR Mathematical Representation

going on (i.e., a different mental model). The probability $p(H_i|z)$ is the confidence placed on each hypothesis (H_i) after the data have been received and considered. All of the variables x, z, and u are vectors (i.e., they can have more than one element, such as positions, velocities, or orientations) and are functions of time (either continuous or discrete), and we wish to model how they evolve and change as new information arrives and time passes.

A hierarchical breakdown of a SHOR model is described, specifiying at each stage the important processes and variables that represent each component. The highest-level breakdown was into SHOR itself. Certain assumptions are implicit in Fig. 3-2, but the main restriction it places on our model is the passing of only state estimates and probabilities (for each hypothesis) between the H and O blocks. These variables were chosen as both sufficient variables for option evaluation and significant results of hypothesis evaluation. They are the primary processes that capture the notion of attaching meaning to the data from the real world, and they answer two essential questions: (1) given a set of possible hypotheses how does the data support or refute each hypothesis? and (2) what does the data imply about the state of the battle assuming each hypothesis is true? The answers to these questions are represented mathematically by the conditional probabilities $p(H_i|z)$ and state estimates $\hat{x}_i$.

Although the primary emphasis of this year's effort is the description of the hypothesis processing, it is important to make certain assumptions about the option evaluation component in order to guarantee the sufficiency of the H component outputs, i.e., only the posterior probabilities, $p(H_i|z)$, and state estimates, $\hat{x}_i$, are necessary to discriminate between alternative actions.

The "best" action is determined by the "minimization" of the risk of losing own-force assets (e.g., the carrier in a battle group). Explicit trade-offs must be made between deploying a platform to prosecute a known threat and creating "holes" in the defense (e.g., increasing vulnerability to the next, as of yet undetected, threat). As a consequence, it is expected that most options will involve the commitment of resources to better determine the situation, i.e., to enable him to discriminate between hypotheses by taking more measurements.

3.2 HYPOTHESIS EVALUATION

The hypothesis evaluation component receives data and hypotheses about the real world and determines whether the data support each hypothesis and what the data imply about the state of the world if each hypothesis were true. For our purposes, a hypothesis is a conjecture about what is going on - it is a <u>model</u> of how the world (or local battlefield part of the world) works and what an enemy intends. It must describe both what is happening and what is about to happen. This, in fact, is similar to the mathematical notion of state, and we define a hypothesis as a mental model of the world in which the model states capture the current information about the world. This model is much smaller than a human's total mental model of the battlefield. The hypothesis may be thought of as a subset of the total model with specific parameters or submodels replacing uncertain components in the larger model.

For example, an expert commander knows how vehicles behave, weapons work, and battles evolve, but he may be uncertain about what an enemy is doing. His hypotheses may be several alternate models of what the enemy is doing, based on components chosen from his experience and his whole model. The hypotheses thus fit within the larger model and yet are more specific, or less uncertain, than the larger model.

The first requirement for the hypotheses is that they be different enough to imply different states that can be observed from the data, i.e., the difference between hypotheses must be both discernible and observable. Two hypotheses that differ only in an insignificant or unobservable detail are not considered. Of course, hypotheses that are consistent with the data at some time but that employ fundamentally different models (e.g., enemy attacks at point A or B when the data indicate he is heading near both) are considered. In fact, most cases of interest involve multiple hypotheses that cannot yet be ruled out by the data but that are nonetheless different.

If the hypothesis is a model of the world, and we wish to estimate the states of the model and the probability of the model's being true given noisy measurements of the world, we are led to consider Kalman filters and multiple hypothesis testing techniques [6;30]. The strength of these techniques lies in their mathematical foundations and adaptability, and both are used for the hypothesis evaluator described below. We are encouraged to use Kalman filters in this context by their successful application to human modeling (in simpler control tasks) in the work of [7;9].

The overall model we propose for the hypothesis evaluation function is shown in Fig. 3-3. Data are passed to a state-estimator component composed of several parallel Kalman filters (one for each hypothesis). Each Kalman filter provides two key outputs: the first is a state estimate based on the data, and the second is the error sequence, δ_i, which is the difference between the

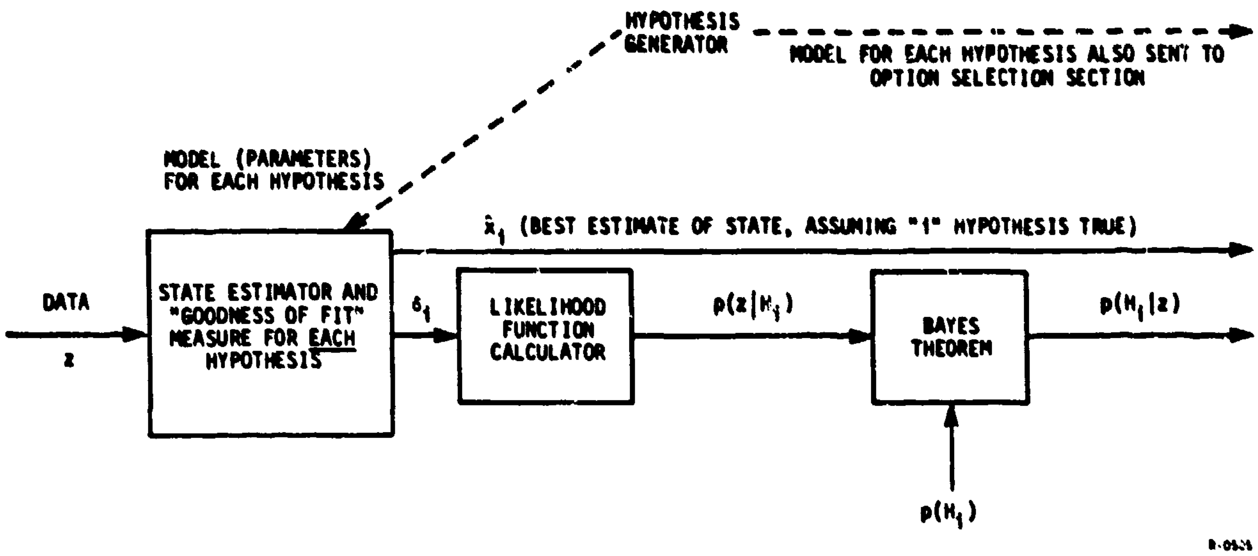

Figure 3-3. Hypothesis Evaluation

measurements and the filter's prior estimates of what the measurements would be. The error sequence is an indication of how well the data match the filter's expectations, and thus provides key information about how the data support each hypothesis. Each error sequence is input to a likelihood function calculator that computes the probability of a data sequence's being observed given that the hypothesis is true. This function is input, in turn, to Bayes theorem, which computes the desired probability $p(H_i|z)$ of the hypothesis's being true.

3.3 COMPONENT DESCRIPTIONS

The above model involves much parallel processing of data: parallel state estimations; likelihood evaluations; and Bayes calculations. Such processing may not be an accurate depiction of how the brain functions, but it does mimic how a commander would simultaneously consider several hypotheses about what is going on, examining how new information support or refute each hypothesis.

3.3.1 Mental Model Implied by a Hypothesis

A conceptual model of the battlefield is shown in Fig. 3-4. The inputs to the world consist of our actions, the enemy's, and nature's. These actions cause the states of the world to evolve, which in turn is measured by us through observations. The measurement process involves only some of the states.

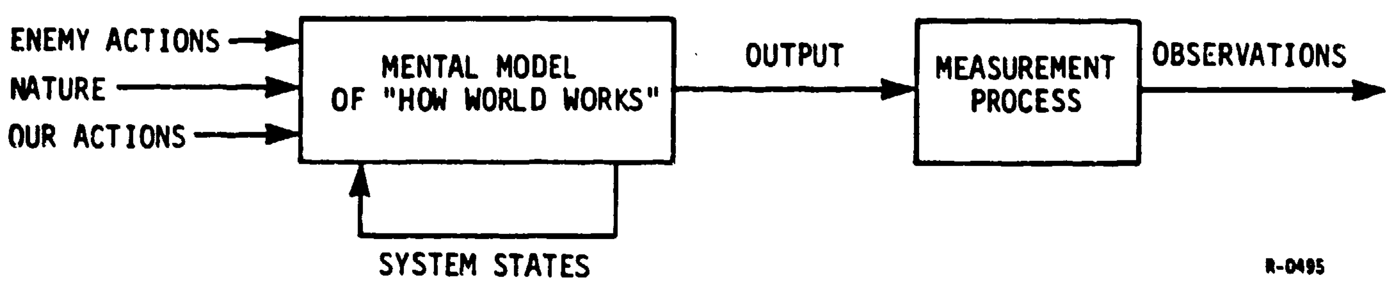

Figure 3-4. Input-Output Model

The general features of a mental model are captured by the specific linear system shown in the vector block diagram of Fig. 3-5. The state of the system is denoted by x, the output, y, observation, z, and inputs, u and w. Of these vector variables, only the input, u, and observation, z, are available to the decisionmaker. The other variables represent an internal characterization of "the way things work." The use of vectors disguises the fact that each of these variables can include many separate elements, such as the positions and velocities of several vehicles in three-dimensional space. The size of these vectors, and therefore the true complexity of the model, needs to be determined for each application. The beauty of the mathematics is that the operations can be described in the compact vector-matrix form, independent of the size of the system.

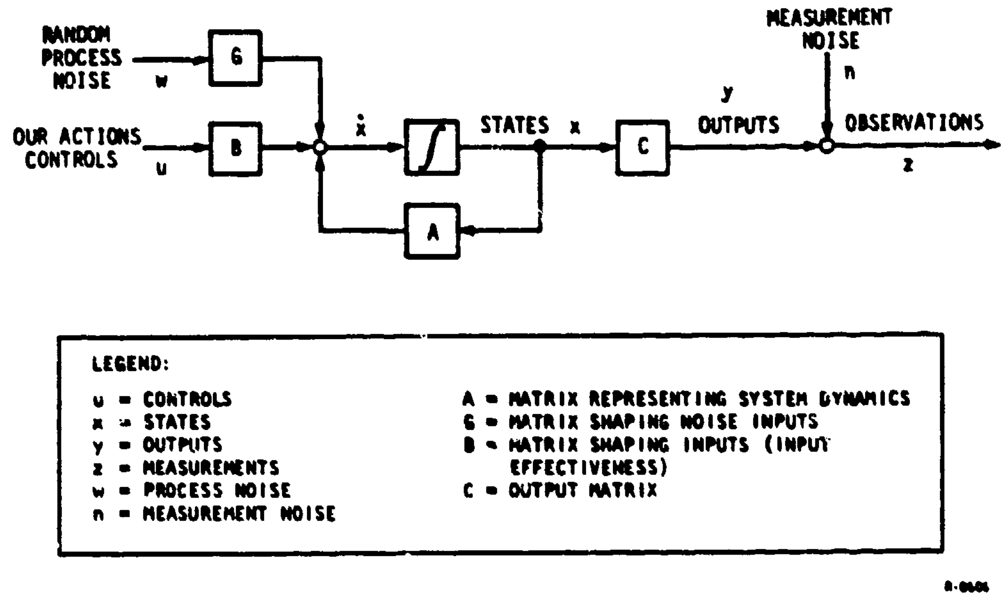

Figure 3-5. Linear System Representation of a Mental Model

This model represents the state dynamics as a linear system, with possibly time-varying coefficients, driven by the decisionmaker's actions and some uncontrolled noise or disturbances, and observed through imperfect measurements. The transformation matrix, C, represents the fact that, even without noise, the entire state of the system cannot be observed, but only a limited number of outputs. The state is the current information needed to predict the future system outputs when combined with future inputs. It summarizes all important current facts about the system.

The parameters of the model are contained in the A, B, C, and G transformation matrices and the noise covariance matrices Q, for the process noise w, and R, for the measurement noise n. The noise processes represent unknown inputs to the system and measurement, and are a convenient way of introducing uncertainty. We need to know the average strength of these processes, but we cannot know the actual values, w and n. In the standard filter, they are represented as white, i.e., flat power spectrum, Gaussian processes, which if integrated would result in Brownian motions. These noises are useful mathematical fictions that introduce input and output uncertainty into the system description, and result in a well-behaved state estimator. Such noise descriptions are reasonably accurate for a wide variety of actual noise processes, and the parameter values are not usually critical, i.e., they do not need to be known precisely.

The model, as shown, represents a continuous-time system, where the variables are considered to be processes changing with time. Kalman filters can also be created for discrete-time systems, where the processes change at specified time intervals. Both static and dynamic C^2 models fit into either of these frameworks.

3.3.2 Kalman Filters for Linear Process Models

Given the linear model above, and using only knowledge of u and z, a Kalman filter is a device for optimally, under certain assumptions, estimating the state of the system. The state estimate is called $\hat{x}$, and the probability density of the error $(x-\hat{x})$, given the measurements, is a Gaussian density with zero mean and covariance P. The estimate $\hat{x}$ is also the mean of the state conditioned on the measurements up to the current time, and the covariance P is the conditional covariance.

The filter has the structure shown in Fig. 3-6, where the optimal gain matrix, K, is given by the equation

$$K = PC^TR^{-1} \quad ,$$

and where the covariance P obeys a Riccati (quadratic) matrix differential equation

$$\dot{P} = AP + PA^T + GQG^T - PC^TR^{-1}CP \quad .$$

The complicated form of this equation obscures the fact that the solution P is guaranteed positive and smaller than it would be without any measurements, i.e., information reduces uncertainty.

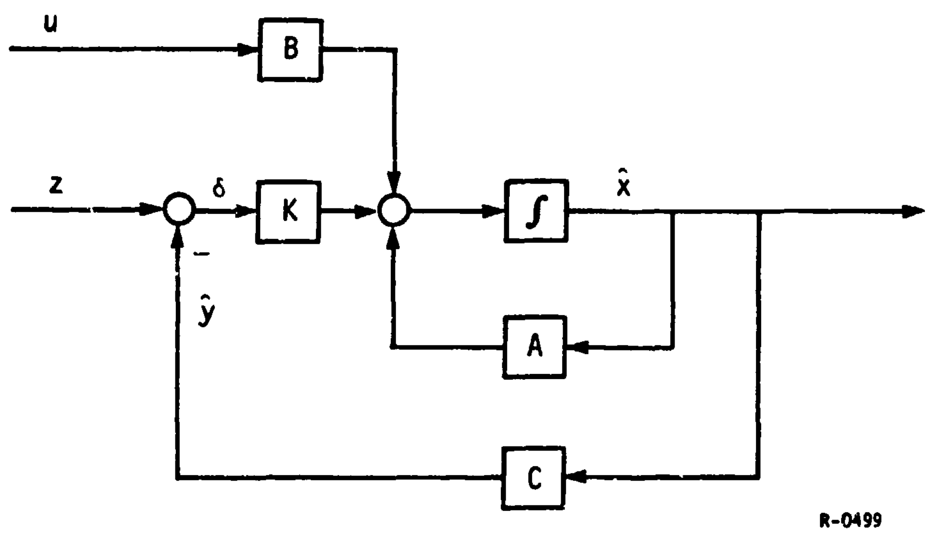

Figure 3-6. Kalman Filter Block Diagram

The filter's operation is characterized in Fig. 3-7. The filter is based on a model of the system, used to predict the system output, and corrected by the instantaneous errors, between the observation, z, and the filter's prediction of the observation, $\hat{z}$.

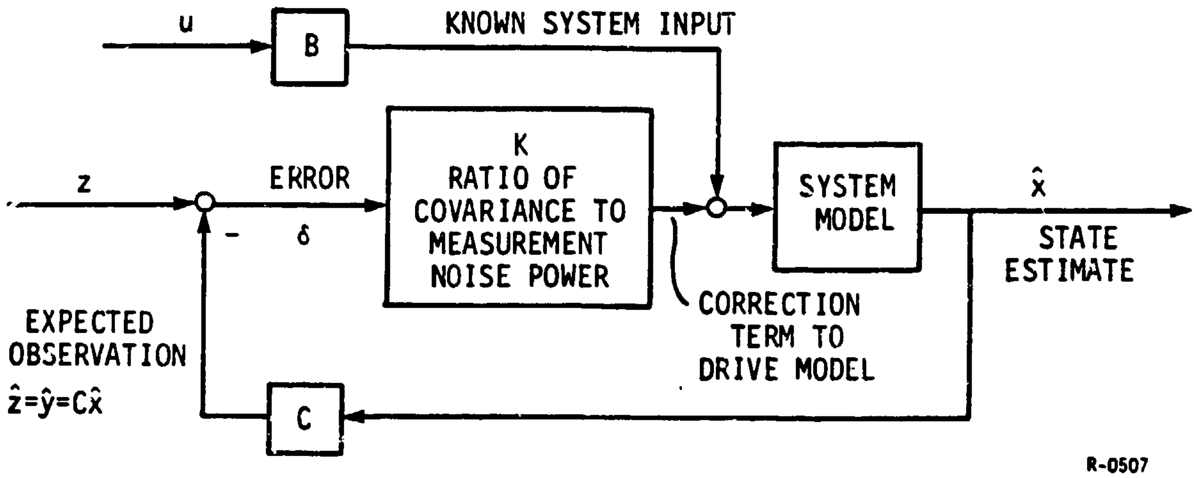

Figure 3-7. Characterization of Filter Operation

Under ideal conditions, the error process, δ, called the innovations or residuals, is a white Gaussian process resembling the measurement noise. Intuitively, if the filter's errors are larger than predicted, we expect that the linear model is wrong. This forms the basis for the hypothesis testing component of our decision model.

3.3.3 Multiple Hypothesis Testing

The hypothesis testing component of the decision model takes the input data and computes the posterior probabilities $p(H_i|z)$, i.e., the probability that each hypothesis is true given the data, z. The calculation of these probabilities uses several Kalman filters - one for each hypothesis. The filter relies on a linear model and parameter set (A_i, B_i, etc.) and computes a best linear estimate of the current state given the measurements. The hypothesis tester uses the innovations from each Kalman filter to compute a new probability for that hypothesis's being true.

To compute the posterior probabilities $p(H_i|z)$ using Bayes theorem, we need the probability

$$p(z|H_i) \quad ,$$

called the likelihood function. For the linear Gaussian models discussed earlier, the important result we will need is that the natural log of the likelihood function, called $\xi_i(t)$, "can be computed recursively essentially by just squaring and integrating the residuals of the feedback term of the optimal filter ..." [6, p. 286]. Let $\delta_i(t)$ be the filter residuals (prediction error) and, for mathematical simplicity in the sequel, assume that $\delta_i(t)$ is available as a discrete-time process, either sampled at $t=k\Delta$ from a continuous filter or available directly from a discrete filter. Let $M_i(t)$ be the error covariance for the filter at time $t=k\Delta$ based on the information (measurements) up to time $(k-1)\Delta$, i.e., the one-step ahead prediction error. Then the log-likelihood function can be computed by the equation

$$2\xi_i(k\Delta) = \xi_{i,bias}(k\Delta) + \xi_{i,observation}(k\Delta) \quad ,$$

where

$$\xi_{i,bias}(k\Delta) = - \sum_{n=1}^{k} \ln\left[M_i(n\Delta) + \frac{R_i}{\Delta}\right] - km \ln(2\pi) \quad ,$$

where m is the dimension of z and

$$\xi_{i,\text{observation}}(k\Delta) = -\sum_{n=1}^{k} \delta_i^T(n\Delta)\left[M_i(n\Delta) + \frac{R_i}{\Delta}\right]^{-1}\delta_i(n\Delta) \quad .$$

The term in the inverse is the expected covariance of the δ_i process if the i-th hypothesis were true; thus a large number for the sum will occur when the δ_i's are large (poor filter performance) and will result in a largely negative $\xi_{i,\text{observation}}$ and, therefore, a small likelihood function, since

$$p(z_{k\Delta}|H_i) = e^{\xi_i(k\Delta)} \quad .$$

This process is shown schematically in Fig. 3-8.

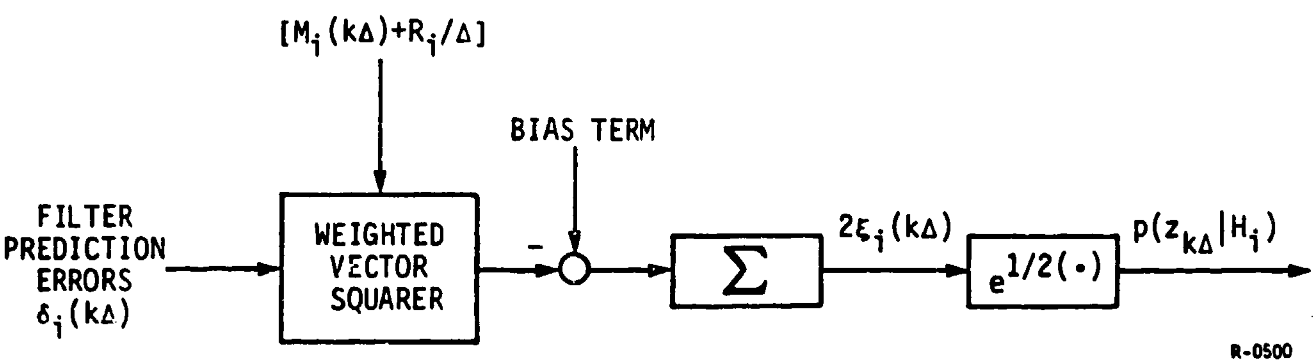

Figure 3-8. Likelihood Calculator

In the above calculator, the likelihood function represents the probability of a given data $z(n\Delta)$, $n=1,\ldots,k$, i.e., occurring given that the i-th hypothesis is true. The diagram indicates how this function is updated as each new data sample arrives. The next step is to describe how the posterior probabilities $p(H_i|z_{k\Delta})$ are updated.

This update is nominally accomplished using Bayes theorem, which simply states:

$$p(H_i|z_{k\Delta}) = \frac{p(z_{k\Delta}|H_i)p(H_i)}{p(z_{k\Delta})} \quad .$$

$p(H_i)$ is the a priori probability of the hypothesis's being true. For our purposes, this is simply the same as the probability conditioned on data up to the last measurements, $p(H_i|z_{(k-1)\Delta})$. The normalizing probability $p(z_{k\Delta})$ is the same for all hypotheses and is found most easily from the fact that the sum of all probabilities is 1:

$$\sum_{i=1}^{I} p(H_i|z_{k\Delta}) = 1 \quad .$$

Let

$$D = p(z_{k\Delta}) = \sum_{i=1}^{I} p(z_{k\Delta}|H_i)p(H_i|z_{(k-1)\Delta}) \quad ,$$

and, thus,

$$p(H_i|z_{k\Delta}) = \frac{p(z_{k\Delta}|H_i)p(H_i|z_{(k-1)\Delta})}{D} \quad .$$

We show this complete process schematically in Fig. 3-9.

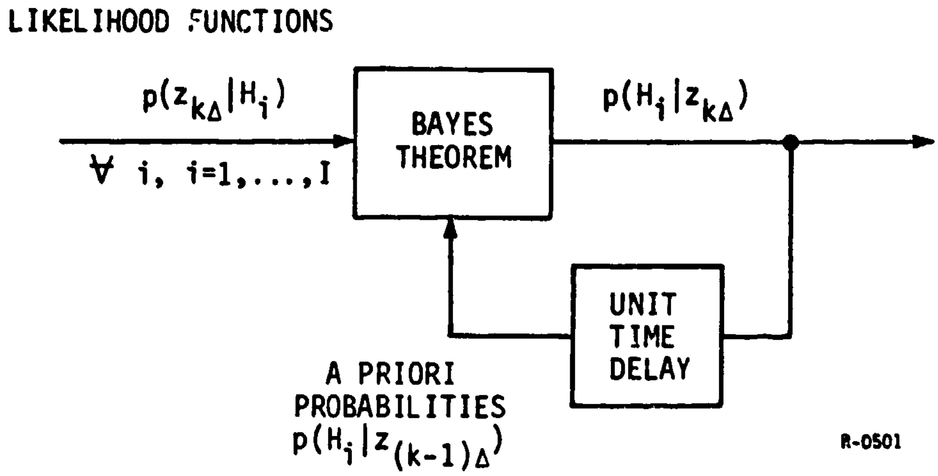

Figure 3-9. Bayes Theorem

3.3.4 Summary of The Modeling Approach

The complete hypothesis evaluation model is shown in Fig. 3-10. For each hypothesis, there is a Kalman filter, likelihood function calculator, and Bayes theorem calculator, which needs the outputs from all likelihood function calculations for normalization.

In many cases, the models for the different hypotheses will be similar, and the above processing can be simplified. The states associated with incontrovertible facts (i.e., hypothesis-independent) could be grouped into a single "meta-model," and the state estimates from the corresponding meta-filter would be passed on to the option-evaluation block. The error from this filter would not provide information about the correctness of any of the hypotheses, and thus would not be passed to the likelihood function or Bayes theorem blocks. Since each of the other hypothesis-dependent filters would now be simpler (of smaller dimension), the resulting likelihood functions and probabilities would be somewhat easier to compute, and mathematically equivalent to the original processing.

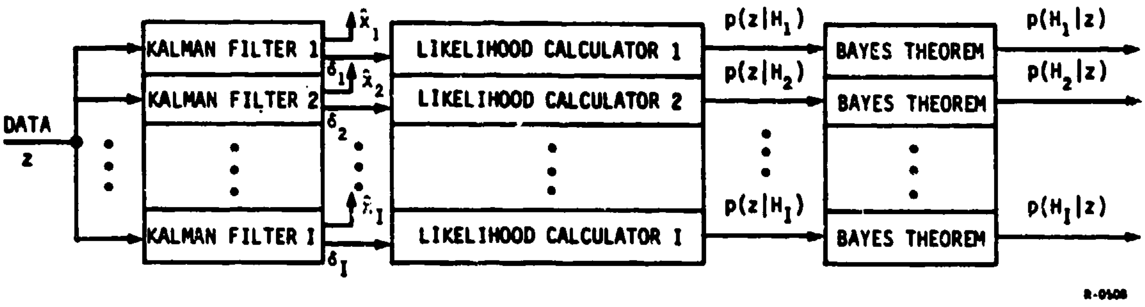

Figure 3-10. Hypothesis Evaluation Model

Although the generation and number of hypotheses are determined elsewhere, the case when only one hypothesis is considered deserves special attention. If one hypothesis is considered, the normalization in Bayes theorem results in a unit probability for that hypothesis. In some cases, this is an accurate model of human behavior, at least for control purposes (i.e., the entire SHOR model will act correctly since the control calculation will be based on the only hypothesis considered). At other times, however, a decision-maker might have only one hypothesis that he recognizes might be wrong. This behavior can be modeled in two ways. The first is to consider a null hypothesis (H_0) corresponding to no state estimate ($\hat{x}_0=0$). The filter for this hypothesis would pass residuals (δ) equal to the data (z) for the likelihood and Bayes calculations. This would result in the probability for his one hypothesis (H_1) being reduced (less than 1) since $P(H_0|z)$ would not be identically zero. In effect, the filter errors from the one hypothesis would be compared with the measurement noise alone.

The second way of examining a single hypothesis is to evaluate the likelihood function against an arbitrary threshold, where, in this case the likelihood function does not use the Bayes theorem normalization. This technique is, in fact, with suitable choice of threshold, similar mathematically to the null hypothesis method, since the division in Bayes theorem involves two likelihood functions. In general, the null hypothesis approach is recommended, but only after determining that only one hypothesis really exists. Often the doubt about the single hypothesis can be represented as a second hypothesis with more structure than the null concept above. The added structure (beyond $\hat{x}=0$) will make the resulting probability calculations much more accurate.

3.4 ANTISUBMARINE WARFARE EXAMPLE

This subsection illustrates how the foregoing hypothesis evaluation component of the SHOR model might apply to a simplified antisubmarine warfare situation: what are the states, measurements, and hypotheses, and how do they evolve? The example considers a task force sailing on an initial course (North in the following figures) during an "alert" condition resulting from higher-level intelligence. The task force commander* believes he is being shadowed by an enemy submarine since he has had several sonar contacts at the

*The functions described in this section are usually carried out as a cooperative effort by the Composite Warfare Commander (CWC) and the ASWC. We shall use the term task force commander (TFC) to represent this joint activity and to distinguish it from actual CWC/ASWC doctrine and tactics, which it is not intended to represent.

trailing edge of his force, although none were confirmed. The situation is illustrated in Fig. 3-11, where the circle represents the "keep-out" range of the task force.

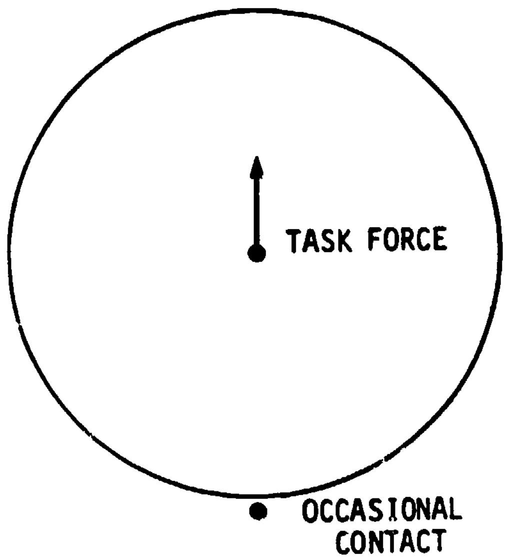

Figure 3-11. Initial Conditions

Initially, the TFC considers three hypotheses.

- H_0: There is no enemy submmarine.
- H_1: There is an enemy submarine trailing the convoy, but he is engaged in simple harassment.
- H_2: There is a trailing submarine, and he is preparing for an attack.

*This notation is used to denote the probability that H_1 is true given all of the data up to an including measurements at time 0.

The subjective probabilities the commander places on these hypotheses at time zero* are:

- $p(H_0|z_0) = 0.45$ (nothing) ,
- $p(H_1|z_0) = 0.45$ (harassment) ,
- $p(H_2|z_0) = 0.10$ (attack) .

(Exact values are unimportant; only grossly relative weights are required).

In this example, the times denote discrete samples approximately 10 minutes apart. The Kalman filter corresponding to each hypothesis predicts where the enemy submarine(s) will be, with time, given past position and velocity measurements.

At time 1, another disappearing sonar contact is observed from the area of the possible trailing submarine. The commander updates his probabilities to be:

- $p(H_0|z_1) = 0.10$ (nothing) ,
- $p(H_1|z_1) = 0.70$ (harassment) ,
- $p(H_2|z_1) = 0.20$ (attack) .

Based on these probabilities, he orders a helicopter to investigate. (The process whereby this decision is made is a subject for investigation next year. The purpose here is to illustrate the evolution of the hypotheses for a given scenario.)

At time 2, there is a second sonar contact, this time ahead of the fleet and about 30° to the starboard. The first helicopter is now in the area of the first (trailing) contact, but cannot find anything. The commander now

*This notation is used to denote the probability that H_1 is true given all of the data up to and including measurements at time 0.

recognizes this attack pattern from war games. He refines the second hypothesis to be:

H_2: Task force under specific type of enemy attack .

He also considers that both sonar contacts could be real, but that the enemy is only engaging in advanced harassment. He considers a new hypothesis:

H_3: Two submarines present, but only harassing .

He updates the probabilities to be

- $p(H_0|z_2) = 0.05$ (nothing) ,
- $p(H_1|z_2) = 0.40$ (shadow-harassment) ,
- $p(H_2|z_2) = 0.45$ (attack) ,
- $p(H_3|z_2) = 0.10$ (two-submarine harassment) .

A major thrust of next year's effort is to develop the option evaluation component of the decisionmaking process. For this example, however, one feasible response would be to dispatch the escort vessel that picked up the new contact to investigate, while preparing a second helicopter for launch. As a precaution, he might order the task force to change direction. The situation is shown in Fig. 3-12.

At this point, we wish to demonstrate how the data can influence the probabilities placed on hypotheses, and the resulting effects on the decisions, by examining three alternate measurements at time 3.

- $p(H_0|z_{3a}) = 0.40$ (nothing) ,
- $p(H_1|z_{3a}) = 0.30$ (shadow) ,
- $p(H_2|z_{3a}) = 0.25$ (specific attack) ,
- $p(H_3|z_{3a}) = 0.05$ (two-submarine harassment) .

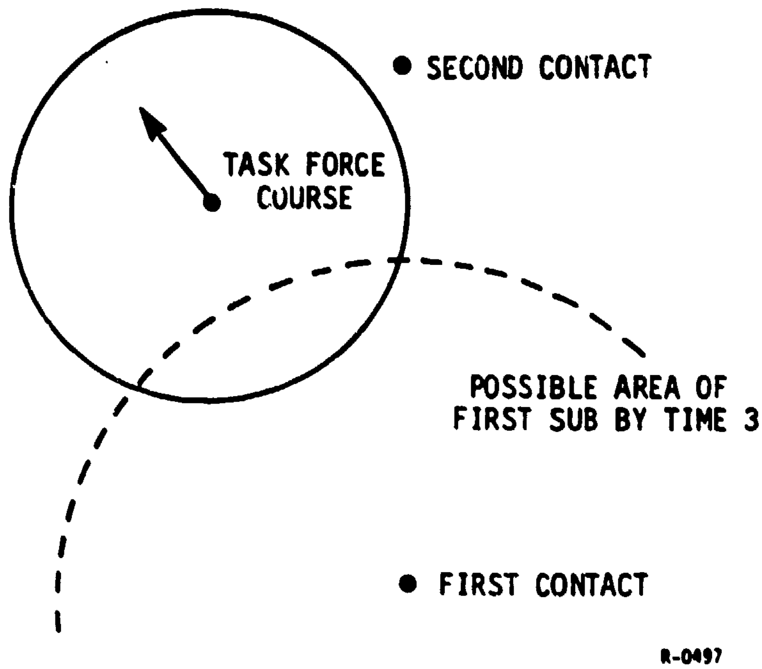

Figure 3-12. Schematic of an Evolving ASW Situation

The ASWC decides to continue on the altered course. If he finds no evidence of either submarine soon, he will resume original course, discarding H_2 and H_3.

In the second case (3b), the new contact is confirmed by the escort vessel. The submarine is identified as an enemy type, and found to be maneuvering for a possible attack. The first submarine has not yet been confirmed, and a fourth hypothesis is added to consider a single submarine (from ahead) attacking:

H_4: single-submarine forward attack .

The updated probabilities become:

- $p(H_0|z_{3b}) = 0.00$ (nothing) ,

- $p(H_1|z_{3b}) = 0.00$ (shadow) ,
- $p(H_2|z_{3b}) = 0.20$ (two-submarine attack) ,
- $p(H_3|z_{3b}) = 0.40$ (harassment) ,
- $p(H_4|z_{3b}) = 0.40$ (single-forward attack) .

The commander decides to arm his weapons and prepare for a solo attack (H_4).

In the third case, both submarines are confirmed and observed to be maneuvering for an attack. The probabilities become:

- $p(H_0|z_{3c}) = 0.00$ (nothing) ,
- $p(H_1|z_{3c}) = 0.00$ (shadow) ,
- $p(H2|z_{3c}) = 0.60$ (two-submarine attack) ,
- $p(H_3|z_{3c}) = 0.40$ (harassment) .

The commander decides to prepare for the attack, arming weapons and possibly changing course.

In these cases, we see how data can force a modification of the hypotheses, greatly influence the probabilities associated with them, and thus influence the decisions made. The role of Kalman filtering in this scenario is almost transparent - simply predicting the expected locations of the submarines assuming the last sightings were real targets. In more complex examples, we expect the filters to play a more important role, predicting more subtle (unobserved) states, and therefore possibly motivating new measurements to observe those states.

3.5 NUMERICAL EXAMPLE

This subsection presents a simple numerical example of the hypothesis evaluation component of the SHOR model to demonstrate how the system parameters affect the probability estimates and their variation with time. The example considers two hypotheses and a simple scalar measurement.* The first hypothesis is that the system state is a scalar first-order Gauss-Markov process driven by white Gaussian noise, and observed with additive white Gaussian noise. This corresponds to an exponential autocorrelation function for the state. The state might represent the increase (or decrease) of enemy probes along a perimeter, and the measurement would be the reported increase or decrease. The second hypothesis is that there are no state dynamics (i.e., $\dot{x}=0$), only measurement noise (i.e., false reports or activity).

The continuous-time model for the first hypothesis (H_1), using the notation of subsection 3.3, is represented by

$$\begin{aligned} A &= -1 \;; \quad G = 1 \;; \\ B &= 1 \;; \quad Q = 1 \;; \\ C &= 1 \;; \quad R = 1 \;; \\ u &= 0 \;. \end{aligned}$$

This system is shown in Fig. 3-13.

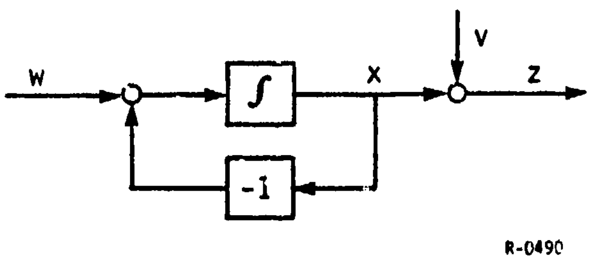

Figure 3-13. First Hypothesis

*The general modeling approach was developed for arbitrarily large vector measurements, states, and inputs. The example of this section is the simplest, scalar case.

The second hypothesis has the parameter set:

$$\begin{array}{llll} A = 0 & ; & G = 0 & ; \\ B = 0 & ; & Q = 0 & ; \\ C = 0 & ; & R = 1 & ; \\ u = 0 & ; & x = 0 & . \end{array}$$

This system is shown in Fig. 3-14.

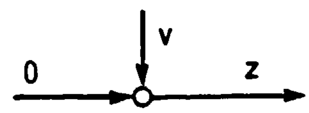

Figure 3-14. Second Hypothesis

The discrete-time version of these systems, which has generally similar behavior (for short sample times Δ), is given by

$$H_1: \quad x_{k+1} = (1-\Delta)x_k + \Delta w_k \quad ,$$

$$z_k = x_k + v_k \quad ;$$

$$H_2: \quad z_k = v_k \quad ,$$

where

$$E[v_k \quad v_j] = \begin{cases} \frac{R}{\Delta} & j=k \quad , \\ 0 & \text{otherwise} \quad , \end{cases}$$

(under both hypotheses) and

$$E[w_k w_j] = \begin{cases} \frac{Q}{\Delta} & j=k \ , \\ 0 & \text{otherwise} \ , \end{cases}$$

under H_1. The noises are independent of each other.

Our hypothesis evaluation model constructs two Kalman filters (one for each hypothesis), given by

$$H_1: \quad \hat{x}_{k+1} = (1-\Delta)\hat{x}_k + \Delta K\left(z_k - (1-\Delta)\hat{x}_k\right) \ ,$$

$$K = P/R \ ,$$

$$\delta_k = z_k - \hat{x}_k \ ;$$

$$H_2: \quad \hat{x}_k = 0 \ ,$$

$$\delta_k = z_k = v_k \ .$$

Under H_1, the gain K is determined from the conditional covariance P, which satisfies the equation

$$P^{-1}_{k+1} = M^{-1}_{k+1} + \left[\frac{R}{\Delta}\right]^{-1} \ ,$$

$$M_{k+1} = (1-\Delta)^2 P_k + \Delta Q \ .$$

For Q=R=1, and for Δ=0.1, this has the solution (in steady-state), when $P_{k+1} = P_k$):

$$P = 0.426 \ ,$$

$$M = 0.445 \ .$$

P denotes the conditional covariance just <u>after</u> a measurement, and M the covariance just <u>before</u> a measurement (i.e., the one-step prediction error). For comparison, the continuous-time variance is given by

$$P = \sqrt{2} - 1 = 0.414 \quad .$$

Thus, little information is lost in the discrete version (Δ=0.1).

We next want to examine how the hypothesis evaluation takes place if H_1 were true. Then the filter above is optimal, and the error process for the first filter has a covariance given by

$$E[\delta^2_{k_1} | H_1] = M + \frac{R}{\Delta} \quad .$$

For the second filter, the error process becomes

$$\delta_k = x_k + v_k \quad ,$$

which has a covariance given by

$$E[\delta^2_{k_2} | H_1] = \overline{x^2} + \frac{R}{\Delta} \quad ,$$

where $\overline{x^2}$ is the covariance of the actual state, found from

$$\overline{x^2} = P_{OL_{k+1}} = (1-\Delta)^2 P_{OL_k} + \Delta Q \quad ,$$

which in steady-state, becomes

$$\overline{x^2} = 0.526 \quad ,$$

Using the processing formulas of subsection 3.3, and assuming that the average value of δ^2 is approximated by the expectations above, we can now compute the posterior probabilities $p(H_1|z_k)$ and $p(H_2|z_k)$ with time (as the measurements are taken). In any experiment, the actual values of the error sequences will be noisy, and the probabilities may become more or less accurate. But on the average, we expect them to behave as shown in Fig. 3-15. The figure depicts the first 30 samples of a hypothesis evaluation (H_1 was true) that began with the filters in steady-state, that is, the initial conditions of the covariances were equal to their steady-state values so that no gain transients occurred, and with three initial probabilities for $p(H_1|z_0)$: 0.25, 0.50, and 0.75. In all cases $p(H_2|z_k)$ is simply

$$p(H_2|z_k) = 1 - p(H_1|z_k) \quad .$$

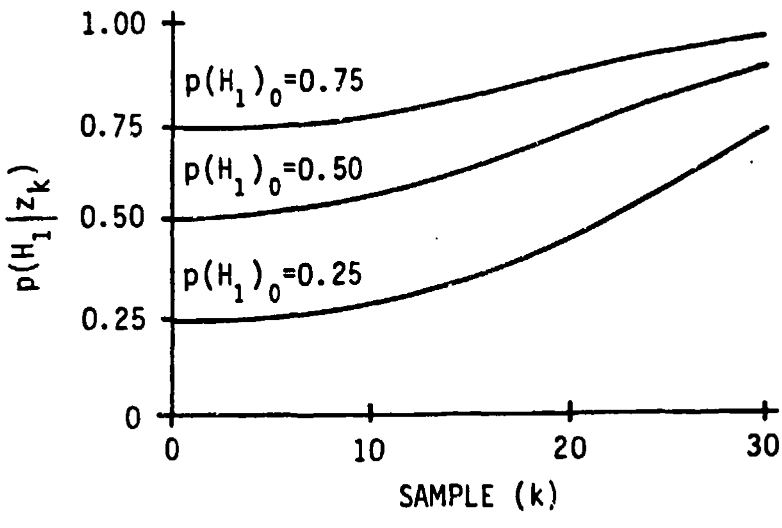

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Figure 3-15. Posterior Probability Variation with Time (H_1 True)

We see that, on the average, the correct hypothesis is chosen reasonably quickly, unless the initial estimate $p(H_1|z_0)$ was poor or the number of samples small. The speed of response of the probabilities is determined by the parameters in the model, through the covariances and initial estimates, and the actual noise samples (data) received. We note that the case where H_2 is true produces similar (symmetric) results for $p(H_2|z_k)$.

3.6 SUMMARY

This section has presented our concept of an expanded SHOR model for human decisionmaking in C^3. SHOR was decomposed into hypothesis and option evaluation components, connected by the state estimates and hypothesis probabilities. A detailed hypothesis evaluation model was then designed that captures the imporant human behavior. An ASW example was presented to illustrate the overall SHOR approach, and a simple numerical example was discussed that demonstrated how the hypothesis evaluation component of the model works.

SECTION 4

DISCUSSION AND RECOMMENDATIONS FOR FUTURE RESEARCH

4.1 DISCUSSION

Summary. The SHOR paradigm was presented as a structure for analyzing human cognitive decisionmaking. The SHOR paradigm describes decisionmaking as a cascading of four activities. They are information processing, hypothesis generation and evaluation, option generation and evaluation, and decision execution.

A model of a commander's hypothesis evaluation activity was developed. The model was cast in the Bayesian (optimal) framework. The inputs to the model are the hypotheses and sensor data, and its outputs are the posterior probabilities of the hypotheses' being true and their respective states of nature. It has been tacitly assumed that these outputs are sufficient for the commander to perform the option generation and evaluation activities.

A brief example of how the posterior probabilities of the hypotheses evolve in the light of new data was presented.

Implications.

1. Based on previous discussions, data are received, identified, and interpreted to have information value by perception processing. The reason, then, to model this process would be an attribution of importance to how preliminary data are interpreted to later modeling efforts, such as decisionmaking or selection. In the ASWC context, sensor data or intelligence information are generally presented to commanders in an unambiguous manner - though it is often uncertain in nature. Such umambiguity precludes the role of perception processing in the modeling effort.

2. In the context of ASW, hypotheses are the existence or nonexistence of target tracks and the target's classifications. All targets are presumed hostile.

3. The Bayesian hypothesis evaluation technique described must be revised to include human limitations and biases. It is improbable that commanders have the cognitive capacity to grapple with the combinatorial complexity requisite for the solution of this algorithm. Nor is there any evidence that they do it in this way.

4. The depth first, one-step backtrack option evaluation algorithm [31] is not suitable. We have learned from conversations with ASW commanders that they do not optimize. They satisfice [32], i.e., they meet some predetermined requirements for action. One commander described the option evaluation activity as "selecting the first feasible action." Some commanders simply adhere to standard operating procedures or doctrine.

4.2 RECOMMENDATIONS FOR FUTURE RESEARCH

Next year's effort will involve the development of a computer simulation of an ASW battle group commander in a hostile environment. The decision problem will be as follows. The ASW commander will be responsible for the tracking, localization, and prosecution of all subsurface contacts to preclude the enemy from coming within range to launch torpedoes or cruise missiles against the carrier. The ASWC will have at his disposal sensors and weapons. These sensors and weapons are components of, or contained on, the battle group's destroyers, attack submarine, helicopters, and carrier-based aircraft.

The seminal activity of the ASWC will then be situation assessment. On a continuous basis, he is asking and trying to clarify these questions [1]:

- Is the datum a false alarm?
- If not, is it an old or new target?
- How can I resolve these ambiguities?
- Which sensor(s) and where to deploy?

- Am I rendering the carrier vulnerable to attack by an, as yet undetected enemy submarine?

The model of the ASWC's decision process will have three major subroutines.

Truth subroutine. This subroutine will model the motion of the battle group's platforms, the status of their sensors, and the motion of the enemy submarines. The inputs to the subroutine will be the ASWC's decisions, overall battle group line of intended movement, and enemy submarine trajectories. The outputs will be the new battle group locations and the data (contacts) generated by the operational sensors.

Tracking subroutine. This subroutine will model the hypothesis evaluation, or situation assessment, activity. That is, sensor data will be related to target tracks. The inputs to the subroutine will be the sensor data and battle group state estimates. The outputs will be the state estimates of the tracks and their posterior probabilities of being true tracks. This subroutine will build upon the work presented in Section 3.

Decision subroutine. The commander's decisionmaking algorithm will be modeled in this subroutine. His controls include the motion and responsibility of ASW platforms. More specifically, he directs the platform movement in space, and platform sensor and weapon status. His decisions will be made on the basis of the perceived threat of the target and the cost (increased vulnerability) of deploying an asset to gather more information. The inputs to the subroutine will be the state estimates of the tracks, the posterior probabilities of being true tracks, and the state estimates of the battle group.

The outputs will be the platform commands. The decision subroutine will encode the satisficing or bounded rationality nature of ASW decisionmaking.

Interviews with experienced ASW players will be held to assess the reasonableness of the model.

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