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PROSPECTS OF A MATHEMATICAL THEORY OF HUMAN BEHAVIOR IN COMPLEX MAN-MACHINE SYSTEMS TASKS*

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SUMMARY

Many useful mathematical models for manual control monitoring and decision-making tasks in man-machine systems have been designed and successfully applied. However, critical comments have occasionally been made, mainly by practitioners concerned with the design of complex man-machine systems. They blame especially models which seem to explain only data from abstract subtask experiments designed particularly for these models.

In this paper, an initial approach to bridging the gap between these two points of view is presented. From the manifold of possible human tasks, a very popular baseline scenario has been chosen, namely car driving. A hierarchy of human activities is derived by analyzing this task in general terms. A structural description leads to a block diagram and a time-sharing computer analogy.

The range of applicability of existing mathematical models is considered with respect to the hierarchy of human activities in real complex tasks. Also, other mathematical tools so far not often applied to man-machine systems are discussed. The mathematical descriptions at least briefly considered here include utility, estimation, control, queueing, and fuzzy set theory as well as artificial intelligence techniques. Some thoughts are given as to how these methods might be integrated and how further work might be pursued.

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INTRODUCTION

When designing such systems as automobiles, aircraft, power plants, and management information systems, it is very important to understand the human's role in the system and design the man-machine interface appropriately. The engineering approach, which leads one to represent the machine in terms of differential equations, networks, etc. suggests that the human can also be represented as a set of mathematical equations for the purpose of systems analysis and design. Thus, considerable effort has been devoted to developing mathematical models of human behavior.

Despite the criticisms of those who find the analogy between humans and equations unpalatable, many models have been reasonably successful within the limited domains that they addressed. In fact, if we accept the premise that human behavior mainly reflects the external environment [1], then it is not surprising that man and machine can be described in similar terms. Quite simply, since the human adapts his behavior to the machine, his actions become somewhat machine-like. (Of course, from a design point of view, one tries to avoid requiring the human to adapt to the machine to any extreme extent.)

On the other hand, the success of models in limited domains has not had substantial impact in realistically complex domains. For example, manual control models are not everyday tools for the aircraft designer. Further, as the reader will see manual control models capture only a small portion of the <u>total</u> task of driving an automobile. For these reasons, designers have been known to claim that mathematical models of human behavior are not particularly useful. While the authors only partially agree with this opinion, even as it relates to currently available models, such statements have motivated the work upon which this paper is based.

Within this paper, the authors present a realistically complex task (i.e., automobile driving) and illustrate the various aspects of the task by using written protocols of subjects' behavior. A hierarchy of human activities is derived by analyzing this task in general terms. A time-sharing computer analogy and block diagram are presented. Numerous mathematical methodologies appropriate to representing such a model are discussed. Finally the state-of-the-art is summarized and the prospects are considered.

A REALISTIC TASK

In considering alternative realistic task domains, the authors discussed a variety of domains including aircraft piloting, industrial process monitoring, and automobile driving. After substantial discussion, it became quite clear that the domain to which both the authors and potential readers could most relate was automobile driving.

The "experiment" involved a hypothetical trip from the driveway of one author's house (GJ) to the home of the other author (WR). Two subjects participated (GJ and WR). Their task was to explain in detail what they would be doing throughout the hypothetical trip. Each subject independently generated a written protocol of the trip. The two resulting protocols were merged to produce Figure 1.

The activities in this figure can be categorized into several levels of behavior:

1. Reaching, twisting, and listening
2. Steering, accelerating, and braking
3. Looking around and estimating
4. Updating and evaluating
5. Planning
6. Reflecting and daydreaming

The authors would like to suggest that a theory of human behavior in realistic tasks should be able to model levels 1 through 5. In pursuit of this possibility, this list was somewhat compacted to yield the following aspects of behavior to be modeled:

1. Sensing and interpreting inputs
2. Planning
3. Implementing plans

To consider these three topics, an overall framework will be discussed in the next section and then, specific approaches to modeling will be considered in the subsequent section.

STRUCTURAL DESCRIPTION

Looking at the hierarchy of human activities discussed above as information processing activities, a time-sharing computer analogy seems to be a very appealing approach to understanding the structural interrelationships.

Figure 2 shows a sketch of such a time-sharing computer analogy. There are several possibilities for the central nervous system (CNS) to interact with the peripheral input and output devices (i.e., the sensory and the motor systems including speech generation). The CNS is viewed as being divided into an operating system and four classes of jobs," i.e., program/data files (see, e.g., [2], [3]). Hereby, a multi-processor system allowing a mixture of parallel and serial information processing is most likely to be a reasonable assumption for the human operator [4].

The operating system is responsible for scheduling the programs in a time-shared manner by using a priority interrupt policy. Conflicting criteria with respect to priority have to also be evaluated by the operating system. This might be a crucial task, especially in urgent situations.

Figure 1: Protocol for Typical City Trip

INSERT KEY IN IGNITION

PUT ON SEAT BELT

PRESS GAS PEDAL TO FLOOR AND ALMOST TOTALLY RELEASE

TURN KEY

LISTEN FOR ENGINE SOUND

IF SO, THEN GIVE GAS

ELSE, STOP AND GO BACK TO TURN KEY

WAIT FOR CAR TO WARM UP - DAYDREAM

LOOK AROUND - SEE IF I CAN BACK UP OKAY - INCLUDES USING MIRRORS

IF SO, THEN PUT CAR IN REVERSE

ELSE, WAIT FOR ALL CLEAR

PUT RIGHT ARM ON SEAT BACK SO AS TO SEE BETTER

STEER WITH LEFT ARM, ACCELERATE AND BACK ONTO STREET

DETERMINE WHEN CLEAR TO GO FORWARD - STOP BACKING UP - PRESS BRAKE

PUT CAR IN DRIVE

LOOK AROUND - SEE IF I CAN PROCEED

IF SO, ACCELERATE

ELSE, WAIT FOR ALL CLEAR

LIMIT SPEED SINCE STOP SIGN COMING UP - CONTINUE LOOKING AROUND

STEER SO AS TO STAY "SORT OF" IN LANE

ESTIMATE DISTANCE TO STOP SIGN - CHECK FOR TIME TO DECELERATE

IF SO, REMOVE FOOT FROM GAS AND OVER TO BRAKE

ELSE, UPDATE ESTIMATE OF DISTANCE - CONTINUE LOOKING AROUND/STEERING

TURN ON LEFT DIRECTIONAL

WHEN FAIRLY CLOSE TO STOP SIGN, PUSH BRAKE HARDER AND STOP

LOOK LEFT AND RIGHT FOR TRAFFIC

IF NONE TOO CLOSE (ESTIMATE IF I CAN MAKE IT). ACCELERATE, TURN LEFT

ELSE, WAIT FOR ALL CLEAR AND CONTINUE UPDATING ESTIMATES

STRAIGHTEN OUT SO AS TO KEEP "SORT OF" IN LANE

ACCELERATE, BUT NOT TOO MUCH BECAUSE STOP SIGN COMING UP

LOOK AROUND AT TRAFFIC - ALSO AT HOUSES AND YARDS - DAYDREAM

EXECUTE STOP SIGN ROUTINE - ONE FOR STOPPING - ONE FOR STARTING

- USE FOUR-WAY STOP SIGN ROUTINE

EXECUTE ENROUTE ROUTINE - INCLUDING TALKING, SIGHTSEEING, ETC.

.

.

PLAN ROUTE - WHAT STREETS TO TAKE

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EXECUTE STOP SIGN/STOP LIGHT/TURNING/PASSING/LANE CHANGING ROUTINES

LOOK AROUND FOR APPROPRIATE PARKING SPACE

IF ONE FOUND, DETERMINE PLAN FOR GETTING INTO IT

ELSE, CONTINUE LOOKING - CONTINUE LOOKING AROUND AND STEERING

EXECUTE PLAN OPEN-LOOP, WITH FINAL UPDATES AS ERRORS CAN BE ESTIMATED

PUT CAR IN PARK

TURN OFF RADIO HEATER, ETC., IF APPROPRIATE

TURN OFF KEY

REMOVE KEY

The four classes of program/data files relate to a central-nervous representation of tasks the human operator has to perform. Each of these program classes is structured into main programs and interrelated subroutines.

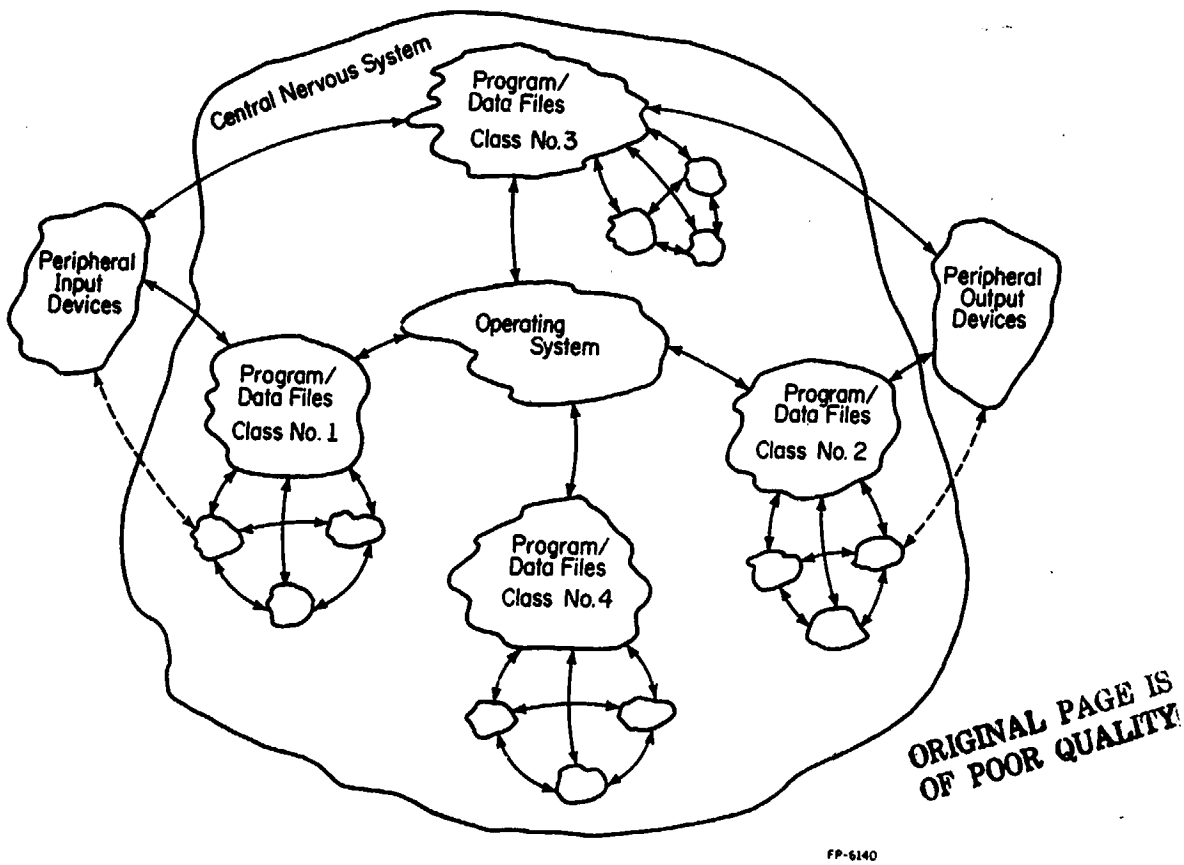

Figure 2: Sketch of a Time-Sharing Computer Model of the Human Operator

Class No. 1 comprises input-related programs, e.g., human monitoring tasks and looking around procedures. Class No. 2 is similarly related to output activites, e.g., the structural organization of motion patterns (e.g., in reaching) and speech. Class No. 3 programs describe strict input-output relationships as in tracking-type control and choice-reaction tasks. All three classes contain programs with a high level of autonomy, perhaps carried out by peripheral processors. The operating system has to initiate and supervise these autonomous processes. Additionally, the adaptive control of the sampling process in parallel tasks has to be accomplished by the operating system.

Class No. 4 represents the long-term memory of the human which includes a knowledge base of facts, models, and procedures. The programs of class No. 4 are concerned with internal processes such as reflecting and planning which have access to the knowledge base, thereby occasionally

modifying it. The operating system is responsible for searching through the knowledge base (see, e.g., [5], [3]).

The time-sharing computer analogy outlined here is mainly assumed as a possible framework for future thinking about complex man-machine systems. To further illustrate the hierarchical multi-level structure of human activities within this framework, a block diagram is shown in Figure 3. Only the most important information flows between the different levels are outlined.

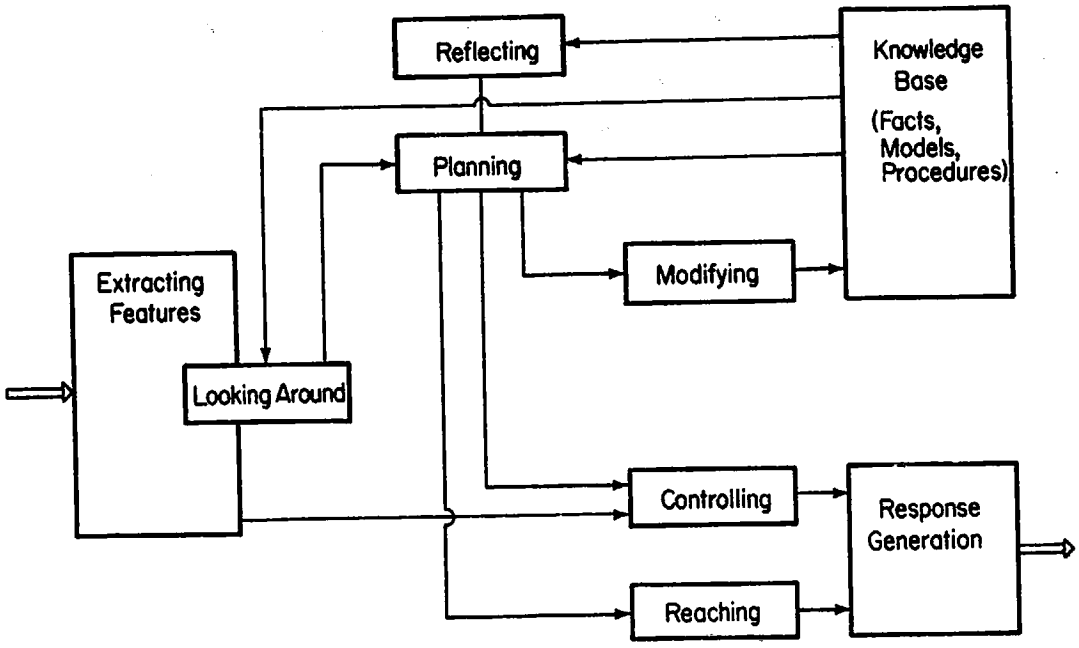

Figure 3: Hierarchical Multi-Level Structure of Human Activities

Lower level processes (bottom of Figure 3) are normally characterized by events occurring at a high frequency as compared to higher level processes (top of Figure 3). This refers to different time scales for different levels. However, because lower level processes may be autonomous, the difference in time scales does not mean that these processes have to be considered by the operating system more frequently.

In Figure 3, planning is denoted as a major activity. With data from the knowledge base and those from lower-level looking around procedures, sometimes influenced by higher-level reflecting, planning is the development of procedures to achieve overall goals and subgoals for lower-level processes. Modifying the knowledge base as well as goal-setting for controlling and reaching are shown as examples. Controlling itself is also best described as a multi-level structure, being a subset of the overall multi-level structure of Figure 3. Controlling and

reaching procedures result in output actions of the human operator via response generation which refers to the peripheral output devices in Figure 2. Correspondingly, the peripheral input devices of Figure 2 extract task-relevant features from sensory input information. This process is very closely linked with looking around procedures which are also indicated in Figure 3.

MATHEMATICAL MODELS

Sensing and Interpreting Inputs

Reconsidering the task analysis of car driving, how does the driver recognize stop signs, other cars, children, etc? Could one, at least in theory, develop an algorithm that successfully performs these aspects of driving?

To pursue this question, the literature of pattern recognition and artificial intelligence was considered. Fortunately, the literature in these areas has recently been summarized in the Systems, Man, and Cybernetics Review [6], by Sklansky [7], and in books by Winston [8], [9] for pattern recognition and artificial intelligence respectively.

Two approaches to pattern recognition have received particular attention: statistical methods and syntactical methods. The statistical methods use discriminant functions to classify patterns. This involves extracting a set of features from the pattern and statistically determining how close this feature set is to the a priori known features of candidate classes of patterns. The class whose features most closely match the measured features is chosen as the match to the pattern of interest, with of course some consideration given to the a priori probabilities of each class and the costs of errors.

The syntactic methods partition each pattern into subpatterns or pattern primitives. It is assumed that a known set of rules (a grammar) is used to compose primitives into a pattern. One approach to recognizing primitives is to use the statistical approach noted above.

Another aspect of pattern recognition involves image processing. Here, each picture point (pixel) is classified according to gray level. Then, thresholds are used to segment the picture. More elaborate approaches use multi-dimensional classification of each pixel and then, use an appropriate multi-dimensional clustering of similar pixels.

Artificial intelligence researchers have devoted considerable effort to scene analysis. With emphasis on understanding scenes composed of somewhat arbitrary collections of blocks, methods have been developed to pick particular blocks out of scenes, even if the desired block is partially hidden.

Most of the methods discussed above have worked reasonably well within limited domains. When the context within which one is working is well-understood, it is often possible to successfully sense and interpret

inputs, although considerable computational power may be needed.

While the advent of inexpensive microelectronics might allow one to utilize large amounts of computational power in a model of human sensing and interpretation of data, there are bigger problems to be solved. Namely, it is difficult to deal with realistic contexts in a static manner. What a human sees depends on what he is looking for, what he expects to see, and the costs of not seeing it. These aspects of seeing cannot be considered out of context and without reference to the specific individual involved.

Several investigators have considered the issue of how the human allocates his attention among multiple displays [10], [11], [12], [13], [14]. However, these models have only been tested in fairly well-structured situations and thus, are as yet unproven in realistically complex tasks. Further, it is by no means obvious that these models will ever be able to handle looking around in the sense it appears in the driving scenario.

Thus, a general mathematical theory of human sensing and interpreting of inputs is far from available, especially if one would like to program this theory to drive a car. On the other hand, the disciplines of pattern recognition and artificial intelligence are beginning to succeed in specific applied domains such as industrial inspection [15], [16] and medical diagnosis [17]. Perhaps a concatenation of specific successes will lead to new insights into the problems of context and individual differences.

Planning

Studying the task analysis of car driving, it is readily apparent that much of the subjects' conscious activities were devoted to developing, initiating, and monitoring plans. This observation agrees with analyses of verbal protocols in several other task domains [1]. In fact, one might expect this result within any purposeful activity for which there are goals as yet unfulfilled.

To discuss planning, one first must emphasize the distinction between the process of developing plans and the process of executing plans [18]. Within this section only plan development will be considered, while the following section will discuss plan execution. One way to illustrate the difference between these two activities is to characterize plan development as a problem solving activity, while plan execution is looked at as a program execution activity [1].

One develops a plan in hopes that its execution will achieve some goals. While one usually accepts the overall goal as given (e.g., land the aircraft), the process of developing subgoals is often left to the human. The partitioning of goals into subgoals and then subgoals into lesser subgoals, etc. reflects a hierarchical mode of planning that has received considerable attention [19], [20].

The hierarchical approach allows one to develop plans that are broad and sketchy as opposed to detailed and concise. Thus, low level subgoals can be temporarily ignored until their immediacy demands attention. Similarly, future actions which require preconditions that are not as yet assured can perhaps be temporarily ignored if one feels that the environment is hospitable to one's goals [20].

On the other hand, low level subgoals must eventually be dealt with. Then, a concise system dynamics model such as Carbonell's probably provides a reasonable description of human behavior [21]. This model assumes that the human is dealing with a system describable by quantitative state transitions and amenable to quantitative control actions.

Such low level planning is probably unconscious. From the perspective of a computer analogy, one might say that high level conscious planning is like executing an interpreted program. (An interpreted program is one where the computer consciously has to interpret the meaning of each statement as it is executed.) On the other hand, low level unconscious planning is similar to executing a compiled program [1]. In fact, it might be claimed that low level planning cannot really be called planning. Instead, such activities are only the details of implementation, which are discussed later in this paper.

Planning appears to include the following aspects:

1. Generation of alternative plans,
2. Imagining of consequences,
3. Valuing of consequences,
4. Choosing and initiating plan,
5. Monitoring plan execution,
6. Debugging and updating plan,

where the latter three aspects deal with observing plan execution and subsequent replanning, but <u>not</u> with actual implementation.

How might one model the generation of alternative plans? One can look at a plan as a linked set of subplans [20]. However, at some level, subplans must be specific. In many tasks, the alternatives are clearly defined at the outset. On the other hand, there are many interesting tasks (e.g., engineering design) where the human must create alternatives. In such cases, humans usually first consider alternatives that have been successful in previous situations.

One might use Newell's pattern-evoked production systems as a model of how the human accomplishes this search for alternatives [1]. A production is a rule consisting of a situation recognition part that is a list of things to watch for, and an action part that is a list of things to do. (The word "production", as it is used here, has absolutely nothing to do with the manufacturing connotation of the word.)

As an alternative to production systems, the idea of scripts might provide a reasonable model, "A script is a structure that describes appropriate sequences of events in a particular context" [22].

The ideas of production systems and scripts are both related to the idea of the human having an internal model. However, as the reader will see, it is very different from the type of model assumed in the system dynamics domain. Namely, productions and scripts provide forecasts of typical consequences rather than models of internal state transitions.

Sometimes a new alternative is needed and it is very difficult to say how a totally new idea is generated. Linking the idea of associative memory [23], [24] with the idea of production systems or scripts, one can conjecture that new ideas are generated when the criterion for matching the new subgoal with past experiences is relaxed and/or non-standard features of the situation are emphasized.

Long-term plans that will not be immediately implemented are probably developed at the highest level in the goal hierarchy with only major goals considered. Such a plan might be a somewhat vague verbal statement or perhaps a sketch of activities and relationships. It is interesting to speculate upon (and perhaps research) what plans look like in the "mind's eye." For example, are plans list-like or are they more spatial, such as Warfield s interpretive structural models [25].

Short-term plans that will require immediate implementation cannot be quite so sketchy. In this case, the human has to consider specific actions. One would probably be reasonably successful in modeling this type of plan using production systems. In this case, specific features of the environment would automatically evoke particular responses. This type of behavior falls into the category of class No. 3 programs as defined in the time-sharing computer analogy introduced earlier. Realistic examples of application of this idea include aircraft attitude instrument flying [26] and air traffic control [27].

Given a set of candidate plans, the human must forecast or imagine the consequences of implementing each plan. One might assume that the human performs some type of mental simulation of the plan. For example, the human might use his current perception of the system dynamics to extrapolate the system s state as a function of planned control strategy. House has developed a model that describes this type of behavior. Succinctly, the model assumes that the human has both a long-term and short-term model of the system with which he is dealing and, that he uses a compromise between the two state predictions obtained from these models as a basis for decision making [28].

However, when plans are sketchy, at least in terms of intermediate preconditions, the human probably does not actually calculate consequences but instead simply maps plan features to previously experienced consequences. Then, until evidence forces him to reject the assumption, he assumes these previously experienced consequences will prevail. This type of behavior is represented quite nicely by the scripts concept [22].

Imagined consequences are then compared to goals. For low level plans, the comparison might be based on a well-defined criterion function. however, this is probably not the case for high level plans. Since high level goals and imagined consequences may be verbal and rather vague, it is likely that the human only tries to satisfice rather than optimize. One might represent this phenomenon using multi-attribute utility functions [29] that have broad optima. Alternatively, concepts from fuzzy set theory [30], [31] might be used to consider the membership of a set of consequences in the fuzzy set of acceptable consequences. The utility function approach is probably appropriate if one assumes that the human has a fairly precise knowledge of the possible consequences, and subsequently values some more than others. On the other hand, the fuzzy set approach would seem to be applicable to situations where the human s perception of the consequences is actually fuzzy.

The human chooses the most satisfactory plan and initiates its execution. If none of the available plans meets an acceptable level of satisfaction, the human either tries to debug the set of plans under consideration or perhaps tries to develop new plans. Debugging of partially failed plans may initially involve local experimentation to determine the cause of plan failure rather than a global reevaluation and complete replanning [32]. One approach to modeling debugging or trouble-shooting of plans is with fuzzy set theory [33].

Assuming that a plan has been initiated, the human monitors its execution and only becomes involved (in the sense of planning) if the unanticipated occurs or execution reaches the point that some phase of the plan must be more concisely defined. Monitoring for the unexpected might be modeled using production systems that trigger when the preconditions are <u>not</u> satisfied. Other approaches, based on filter theory [34] or pattern recognition methods [35], are also available but beyond the scope of the discussion here.

Once the unexpected has been detected, planning might shift into the above mentioned debugging mode. On the other hand, the need to shift from sketchy to concise planning may involve abandoning, for the moment, the broad hierarchical mode and shifting to a detailed partially pre-programmed mode.

How do all these bits and pieces fit into an overall model of planning? While it does seem that the hierarchical approach to planning combined with the production system and script ideas provide a reasonable framework, the state-of-the-art certainly does not allow one to construct a context-free planning model in the form of an executable computer program. This may be an inherent limitation if one accepts the premise that much of human behavior is merely a reflection of the task environment [1]. If this premise is true, then one should be very careful that laboratory abstractions capture a sufficient portion of the real world environment and thereby allow results to actually be transferable. Otherwise, one is only developing a theory of human behavior in laboratory games.

As a final comment on planning, a very important issue concerns the level at which one's study of planning behavior should be addressed. While an approach at the neuron level [36] may eventually lead to a successful model of human planning behavior, such an approach is unlikely to lead to success in the near future. Alternatively, one might try to develop models that explain or predict whether or not a plan will be successful. However, this type of model would yield little information about the planning process. It seems that one must approach studies on the conscious planning level using either verbal protocols [1], [37], [38] or at least methods that require plans to be explicitly measurable. Then, the variety of approaches to modeling discussed in this section can be applied to describing the planning process.

IMPLEMENTING PLANS

Implementing plans refers to human action, mainly controlling and reaching in the multi-level structure of Figure 3. Two basic approaches for mathematically describing these actions can be distinguished. The first approach includes time-line analysis, queueing theory, and simulation techniques, whereas the second includes the control theoretic approach in a more general sense.

In time-line analyses, the execution times of all particular task elements of a certain multi-task situation are assessed as well as the total task time needed [39], [40], [41], [42]. Available time margins or expected time pressure of the human operator can be calculated in order to estimate total task system performance and human operator workload. This method has been applied to evaluating rather complex man-machine systems by taking these apart in very much detail, e.g., to the level of reaching times for single switches.

A related but more analytical approach is the queueing theoretic one [11], [12], [43], [44], [45], [46], [47]. It is suitable not only for analysis but also for design purposes. The different tasks of a multi-task situation are considered as customers in a queue waiting to be serviced. Arrival and service rates as well as the waiting time for the tasks are characteristic measures. Service with a priority policy is possible. Also several servers (e.g., the human operator and a computer) may share responsibility for the total task.

Both approaches, time-line analysis and queueing theory, look at the implementation of actions in terms of time expenditure. If the accuracy of the actions is also to be taken into account, these methods have to be combined with others. Simulation techniques seem to be a reasonable approach where micro-subroutines simulate dynamically such human operator behaviors as short-term memory recall and movement of hands and feet [48]. This leads back to the time-sharing computer analogy. A goal-oriented priority interrupt structure for handling all tasks appropriately in a multi-task situation is most promising. However, this results in a more artificial-intelligence oriented simulation, using heuristics and data handling algorithms, rather than an analytical description.

A different approach for the description of human actions in man-machine systems applies control theory. Models for continuous manual control are well established. Numerous summaries in the forms of reports and books exist (e.g., [49], [50], [51]). Most popular are the quasi-linear and the optimal control models. The quasi-linear models describe the human control behavior by some task-specific modification of a generalized transfer function which is best satisfied in the crossover frequency region for many controlled element dynamics. In addition, an internal human noise source (the remnant) summarizes the portion of the human's output which cannot be explained linearly.

The optimal control model [52] includes two noise sources and also has a time delay and a neuromuscular lag term with a time constant similar to that of the quasi-linear model. A Kalman filter estimates the states of the controlled element, whereas a predictor compensates for the time delay. The optimal gains are calculated with respect to a criterion function which is a weighted sum of mean squared values of state and control variables.

The control theory models have been applied in several domains including aircraft piloting, automobile driving, ship piloting, and anti-aircraft artillery. Further, several display design methodologies have been developed. A recent special issue of Human Factors reviews many applications of control theory models [53].

With both the crossover model and the optimal control model, a stochastic reference input, either forcing function or disturbance, has been assumed. Therefore, these models are mostly applicable to the inner loops of manual vehicle guidance and control tasks. In the case of the optimal control model, key elements of this have also been applied to monitoring and decision-making tasks.

Many realistic tasks exist, however, in which deterministic inputs are dominant. Taking the baseline car driving scenario as an example, a more complicated deterministic input exists, i.e., the course of the street. For this task, a two-level model has been proposed which has a closed-loop stabilization controller and an anticipatory open-loop guidance controller working in parallel [54], [55]. The perceptual aspects of the anticipation of changes in the course of the street have been explained. However, it has been assumed that the driver tries to eliminate all deviations from the middle line of the street.

To overcome this simplification, the street might be viewed as a target tube in which the driver is allowed to move his car. Interestingly enough, many other human control tasks in vehicle guidance and industrial process control also require controlling the state of the system within a target tube rather than along a single reference line. Such a criterion makes these tasks much more relaxed than one often assumes in man-machine systems experiments.

Reviewing the control theory literature, some applicable methods for controlling within a target tube were found. They have never been used with man-machine systems problems. One approach assumes a criterion

function which puts less weight on small errors by taking the fourth power of the error instead of the second power as in the optimal control model [56]. The other approach is called unknown-but-bounded control [57], [58], [59]. Figure 4 illustrates how the controller tries to keep the state (X) of the system always in an effective target tube to assure that it will never cross the boundaries of the outer target tube under all expected disturbances.

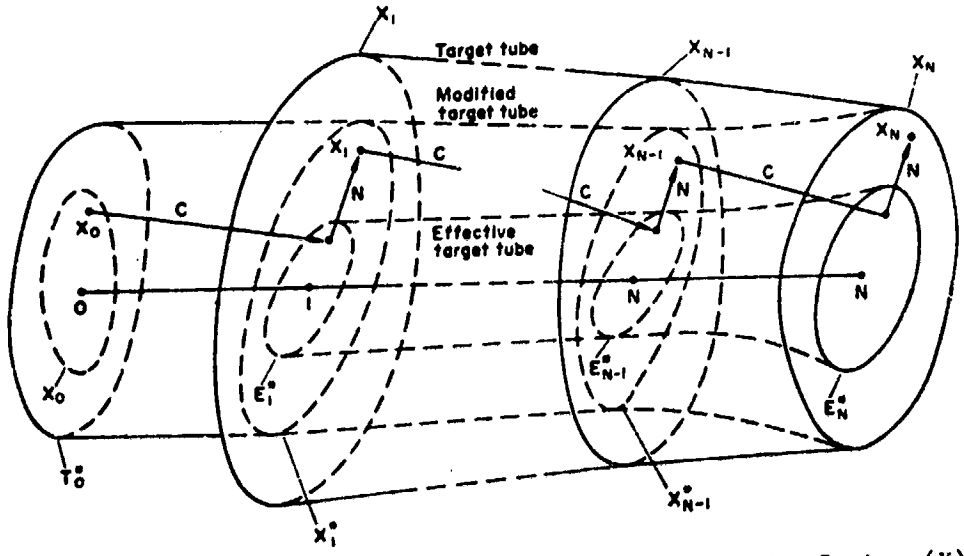

Figure 4: Schematic Presentation of the State of the System (X) as Affected by the Action of the Controller (C) to Counteract Disturbances (N) for Reachability of a Target Tube (from [57])

The unknown-but-bounded control approach combines state variable with set theoretic descriptions. Due to the higher mathematical effort, this approach has infrequently been applied in automatic control situations. However, it seems worthwhile to consider this approach in modeling biological or sociological systems. Human behavior in general is goal-oriented and the goal is very often defined as bringing or keeping some state variables within a certain target set or target tube.

In the baseline scenario, the target tube of Figure 4 would be the width of the street or one of its lanes. The effective target tube is planned by the driver as an area inside of which no control actions are necessary (see linear-plus-dead-band control laws in Glover and Schweppe [58]). Planning the effective target tube might also include some fuzziness. Whether the unknown-but-bounded control approach can be combined with fuzzy set theory which has recently been applied in industrial process control [60] has not as yet been investigated.

Another interesting issue is the notion of the internal model which has been considered to some extent in the discussion of the planning process. In modeling how the human chooses among alternative courses of action, an important issue concerns whether the human possesses a correct

internal model of his environment or, whether the model is incorrect as in learning situations or, very approximative as in large-scale systems (see, e.g., [61]). The process of building up an internal model during learning and how to use it by changing control laws or choosing among different kinds of control laws in time-varying systems, should be further investigated. The literature on adaptive manual control shows, for example, that the models assume a set of predetermined control laws matched with a set of different system dynamics (see e.g., [62]).

This leads to the idea of a memory for motor patterns. Instead of having an input-output transfer behavior, the human operator initializes predetermined motor patterns in many situations. These patterns are slightly corrected during their actual execution (see,e.g., [63]). Good examples are walking, bicycle riding, and piano playing. Also, the coordination and timing of a series of discrete manual control actions, e.g., in trouble-shooting tasks or in checking procedures of aircraft pilots or process operators, can be explained by predetermined motor patterns.

DISCUSSION AND CONCLUSIONS

In considering various approaches to tying all of the discussions in this paper together, the authors found the diagram in Figure 5 to be most useful. This diagram is a variation of a diagram discussed by Johannsen [64] for vehicle control tasks and Sheridan [1976] for human control of vehicles, chemical plants, and industrial robots.

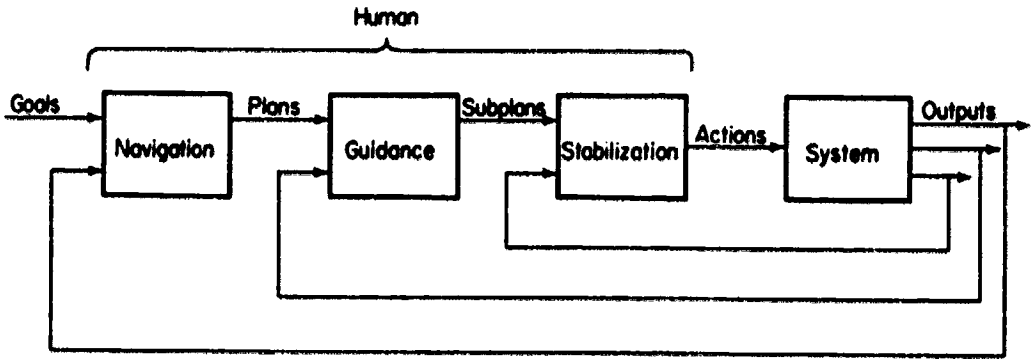

Figure 5: Hierarchy of Human Behavior

This diagram can be used to represent well-defined man-machine systems tasks such as those discussed by Johannsen [64] and Sheridan [65] as well as less well-structured tasks. For example, goals could mean success in life, plans could mean a career outline, subplans could mean a scheme to succeed in a specific job, and actions could mean one's daily activities. Thus, the diagram has broad applicability.

How can one analytically deal with such a general description? If one looks at control theory with a very general perspective that includes control with respect to continuous events as well as discrete events, then one can subsume most analytical methods (e.g., linear systems theory and queueing theory) within the category of control theory. This generalization, and willingness to expand the set of tools one utilizes, enables quantitative analysis of a larger portion of the hierarchy of behavior.

However, there are limits to context-free analytical modeling. First, there is the very important idea that human behavior mainly reflects the task environment. Thus, searching for a specific analytical model of general human behavior may only be fruitful to the extent that all task environments are common. Perhaps then, one should first search for commonality among environments rather than intrinsic human characteristics. In other words, a good model of the demands of the environment may allow a reasonable initial prediction of human performance. Thus, it is reasonable to initially assume that the human will adapt to the demands of the task and perform accordingly.

A second limitation to analytical modeling is due to the human's lack of analytical thinking, especially at upper levels of the hierarchy. First of all, the human is more of a satisficer than an optimizer. Thus, ideas such as a target tube within control tasks, fuzzy set theory, and some concepts from utility theory deserve more study and application within man-machine systems. What this means is that one should look at optimization with respect to broad criteria that allow multiple satisfactory solutions. An alternative approach to this issue is to discard optimization, but this would leave the modeler stripped of one of his most important tools and without a viable alternative.

Beyond the idea of satisficing, another important limitation to analytical modeling is that humans simply do not worry about details until it becomes necessary to do so. Thus, planning can be sketchy, perhaps in the form of scripts. Such sketchy planning can mean a drastic reduction in mental workload and also, that the human has the resources left to deal with more tasks as well as the flexibility to react to unforeseen events. These characteristics are precisely the reasons why humans are often included in systems.

However, the scripts idea presents a problem. While everyone might agree that humans use scripts to expedite performance of many tasks, knowledge of their existence is not sufficient to predict performance. One must know what the script specifically is. Thus, in complex tasks, one must measure not only performance (e.g., RMS error) but also the script.

This suggests that verbal protocols (perhaps analyzed by a computer that understands natural language) may be increasingly important research tools.

To conclude, this paper has presented a fairly general, but mainly verbal, model of human behavior in complex tasks. The ideas discussed have been based on analysis of a specific complex task (car driving) as well as a thorough review of the literature. Three very specific ideas have emerged. First, control should be looked at in a broad sense, incorporating a wide range of analytical methodologies. Second, the human satisfices rather than optimizes and criteria should reflect this. Third, higher-level activities such as planning require approaches that allow incompleteness, and approaches that capture the process of these activities and not just the results.

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