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MATHEMATICAL MODELS OF PILOT-HELICOPTER SYSTEMS

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ABSTRACT

Many piloted aircraft problems can successfully be solved utilizing engineering models of manned aerospace systems. This concerns not only design problems by which these models allow a systematic investigation of the effect of design alternatives on mission success but also operational research questions can be answered on the basis of a profound insight rendered by the model in the complex interaction among mission- and pilot-related variables.

Just because overall system reliability primarily pertains to this complex interaction between pilot functioning and his task environment it is desirable to describe his behavior in terms commensurate with those used for other system elements. The more so as human behavior primarily reflects (adapts to) his task environment it seems a reasonable approach to describe man and machine in similar terms. Of course, this makes only sense to the extent model results are in agreement with the corresponding measures of pilot-helicopter behavior. In other words, the substantial success of engineering models has to be related to the limited domains that they address.

Specifically, in this paper a theoretical framework in terms of state space optimization, estimation and decision theory is reviewed which is sufficiently general to allow the description of meaningful (i.e. relevant with respect to overall system reliability) pilot functional characteristics.
This involves continuous information processing both of display indicators and of the outside world resulting in an internal representation of the task.
In the case of control tasks this information processing model is combined with a control response model. This is known as the optimal control model. Preliminary attemps will be reviewed to address pilot monitoring and decision making as well.

The resulting integrated model of the man-machine system provides measures of pilot workload and system performance. It will be illustrated that the model is a useful tool to deal with many design and operational problems of pilot-helicopter systems.

1 INTRODUCTION

Many design and operational problems of pilot-helicopter systems are related to the human operator's functioning in these systems. Therefore, pilot-related aspects have to be considered when approaching these problems.

One promising approach concerns the use of mathematical models of the total pilot-helicopter system.
Just because overall system reliability primarily pertains to the complex interaction between pilot functioning and his task environment it is desirable to describe human behavior in terms commensurate with those used for other system elements. The more so as human behavior primarily reflects (adapt[illegible] task environment it seems a reasonable approach to describe man an[illegible] in similar terms. Of course, this makes only sense to the extent [illegible]ults are in agreement with the corresponding measures of human behavior. In other words, the substantial success of engineering models has to be related to the limited domains that they address.

In order to treat realistic, complex task situations, the model structure must be multivariable and formulated in the time domain. This theoretical framework is provided by the state space optimization and estimation theory which is sufficiently general to allow the description of meaningful (i.e., relevant with respect to overall system reliability) pilot functional characteristics.

So far, this involved primarily continuous human information processing (resulting in an internal representation of the task) and control behavior as described by the optimal control model (Refs. 1-4). Also preliminary attempts have been made to address human monitoring and decision making as well (Refs. 5 and 6). A block diagram of these human functions in the man-machine system is given in figure 1.

The general structure of the model, however, allows an evolutionary development in order to deal with many pilot-helicopter characteristics. This concerns not only design problems by which the model allows a systematic investigation of the effect of design alternatives on mission success but also operational research questions can be answered on the basis of a profound insight in the complex interaction among mission- and pilot-related variables rendered by the model.

In the next chapter the afore-mentioned pilot-helicopter model will be reviewed. Herewith, pilot functioning will be described according to the various stages of information processing and functional aspects.

Chapter 3 contains an illustrative application of the model demonstrating its predictive and diagnostic capability to describe realistic pilot-helicopter situations. Concluding remarks are made in chapter 4.

2 PILOT-HELICOPTER MODEL

The present pilot-helicopter model is based on the fundamental hypothesis that the well-motivated, well-trained human operator behaves in a near optimal manner subject to his inherent constraints and the extent to which he understands the objectives of the task. This implies that the description of pilot behavior is concentrated on two aspects:

(subjective) criteria for optimality and the human limitations.
In addition, it is assumed that the human operator is dealing with a linear system. Although, strictly speaking, such a system does not exist, the behavior of many systems can be described by linear differential equations, often after some linearization scheme (assuming small perturbations around a trim condition, describing function techniques, etc.).

Once these assumptions are made, linear optimization and estimation theory can be used to formulate the foregoing notions. This is described in the following sections.

2.1 System description

The helicopter system (in general the controlled process) is mathematically represented by a vector linear differential equation

$$\dot{x} = Ax + Bu + Ew \tag{1}$$

where x is the vector of the system states (helicopter variables of interest), u is the vector of pilot control inputs and w is the vector of linear independent, Gaussian, white noises (system disturbances, e.g., turbulence). This linear(ized) system comprises the basic helicopter system, any dynamics associated with measurement, control and display systems as well as the environmental disturbances. In case the human operator is not actively engaged in the control loop and only monitors the automatic system, B=0 in eq. (1).

It is assumed that the display variables y are linear combinations of the state and control variables (the word display refers to visual cues both from instruments and from the outside world; in general, also aural and vestibular cues can be included)

$$y = Cx + Du \tag{2}$$

The matrices A, B, C, D and E of eqs. (1) and (2) may be constant corresponding with a given flight condition and display situation. On the other hand, also time variations in system dynamics, disturbance and display characteristics can be treated on a piece-wise constant basis over a given interval. The controlled system and displayed information are shown in the man-machine model representation of figure 2.

For a stationary process system performance can be expressed in variances and probability measures of all system variables of interest. Also frequency domain measures can be obtained such as human describing functions, remnant (see section 2.2), and power spectra of all system variables (Refs. 1 and 2).
In case of deterministic inputs and time-varying characteristics of the task environment, such as gust disturbance variations, windshears, variations in displayed information, vehicle dynamics and task instructions (e.g., different mission segments, approaching the runway, etc.) the time-average measures are not applicable.Now performance is conveniently described by means of covariance propogation methods. Statistically, this implies ensemble-averaging.

2.2 Human operator model

Human operator functioning in the afore-mentioned pilot-helicopter

system will be described according to the various stages of information processing shown in the block diagram of figure 2. The first stage concerns the perception of displayed information and is discussed in paragraph 2.2.1. Basically, this amounts to a relationship between the display variables y and the perceived variables y_p.
In paragraph 2.2.2 it is described how this perceived information is (optimally) utilized to update the present knowledge about the dynamic process. This knowledge is based on all past data and the (learned) system dynamics. The result is an internal representation (internal model) of this dynamic process. This internal model described how well aware the human operator is of the various system states which directly pertains to human monitoring (discussed in paragraph 2.2.5).
Pilot's responses (if applicable) are also based on this information ...imation of the system state). The optimal response selecti... ...sponse execution are described in paragraph 2.2.3 by the control response model. In this combination the foregoing (sub)models are known in the literature as the optimal control model (Refs. 1-3).

The aspect of human controller's workload, indispensable for a complete description and prediction of human control behavior and its impact on mission success, is taken into account by the workload model discussed in paragraph 2.2.4. Because of the adaptive human capabilities, wordkload is often the most sensitive to task characteristics under consideration.

Also human monitoring and decision making can be crucial functions to fulfil, especially in view of increasing complexity and automation of aerospace vehicle. Decision making which is also based on the information provided by the internal model of the dynamic process, is described by the model discussed in paragraph 2.2.5.

2.2.1 Perceptual model

The perceptual model (see figure 3) indicates how the perceived variables y_p are related to the "displayed" variables y according to

$$y_p(t) = y(t-\tau) + v_y(t-\tau) \tag{3}$$

where τ is a lumped equivalent time delay, representing the various internal time delays associated with visual (or aural, vestibular, etc.), central processing and neuromotor pathways. The various sources of human randomness (unpredictable in other than a statistical sense) are represented by errors in observing and processing information. This lumped noise v_y is assumed to be an independent, zero-mean, Gaussian, "white" (wide-band) noise process. Each element of v_y is, therefore, specified by its autocovariance V_{y_i}.
This autocovariance is a key parameter of the pilot model. It has been found (Ref. 7) that this autocovariance scales with the signal variance $\sigma^2_{y_i}$ (in accordance with the Weber-Fechner law). In addition, it can be related to the fraction of attention f_i, dedicated to variable y_i (Ref. 8): the autocovariance appears to be inversely proportional to f_i. This can be interpreted as a parallel information processing mechanism (capacity model), but also as a time-sharing mechanism (Ref. 9). In the latter case f_i represents the fraction of time attended to variable y_i. The same reference shows that f_i can also be interpreted as the probability that the human operator will be attending to y_i.

The autocovariance is given by

$$V_{y_i} = \frac{P_o \, \sigma^2_{y_i}}{f_i \, K_i^2} \tag{4}$$

where P_o is the "noise-signal" ratio and has units of normalized power per rad/s (over positive frequencies). A typical numerical value for P_o of $0.01\,\pi$ has been found for well-designed displays. This relatively constant value suggests a basic, primarily human operator-related characteristic. It reflects a given amount of attention (or fraction of time, etc.) dedicated to the task and is an essential part of the workload model discussed in paragraph 2.2.4. The quantity K_i is the describing function gain associated with a threshold. This can represent a perceptual threshold, but also "indifference" thresholds can be accounted for (i.e., within certain bounds the human operator disregards the displayed information). Furthermore, the threshold can be related to other viewing phenomena such as signal reference characteristics. This is especially important when describing the perception of the outside world information.

2.2.2 Information processing model

Based on the perceived data y_p up to time t and the learned dynamics of the system, the best (least-squares) estimate ($\hat{x}$) of the system state (x) is made (Fig. 3). This concerns the situation at time t-τ (due to the time delay). A predictor provides the best estimate at time t. Leaving, for the sake of discussion, the delay out of consideration the resulting internal representation (estimate $\hat{x}$) of the task (state x) is given by (see also figure 3)

$$\dot{\hat{x}} = A_c\hat{x} + K(y_p - C\hat{x}^{*}) \tag{5a}$$

where A_c represents the closed loop system dynamics (in the case of control; when dealing with an automatic system $A_c \rightarrow A$) and K is the Kalman filter gain which is optimally adjusted, i.e. the best use is made of new information y_p. This can be illustrated by an alternative expression for equation (5a) by combining equations (2), (3) and (5a)

$$\dot{\hat{x}} = A_c\hat{x} + K(Ce + v_y) \tag{5b}$$

with

$$K = \Sigma C' V_y^{-1} \tag{5c}$$

where $e = x-\hat{x}$ is the estimation error and Σ is the variance of e. Equation (5b) indicates that the present knowledge of the system ($\hat{x}$) is updated on the basis of new information (e) disturbed by noise (v_y). Equation (5c) shows that more emphasis is placed on new information when the uncertainty about the system is large and the new information is reliable. In other words, K is large when Σ is large and V_y is small.

In equations (5a)-(5c) it is assumed that the human operator "knows" ("has learned") the dynamics of the system (A_c). Although this assumption is questionable for complex systems this model has worked well in many applications.

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* Stricktly speaking, also including the estimated control variables.

2.2.3 Control response model

Pilot control response can be divided in the selection and the execution of the response (Fig. 4).
The response selection is assumed to be generated by a control command process which is represented by a set of optimal gains, L, operating on the estimated state, $\hat{x}$, according to

$$u_c = - L \hat{x} \tag{6}$$

These gains, L, are optimal in the sense that they minimize (in the steady-state) the performance index

$$J(u) = E \{ y'Q_y y + u'Q_u u + \dot{u}'Q_{\dot{u}} \dot{u} \} \tag{7}$$

where the quadratic cost functional $J(u)$ reflects the objectives of the task and Q_y etc. are the cost functional weightings which can depend on objective and subjective factors (Refs. 1-4).
Pilot control response is executed according to (Fig. 4)

$$T_N \dot{u} + u = u_c + v_u \tag{8}$$

indicating how the commanded control, u_c, results in the actual control input, u. Herein, T_N is the "neuromotor" lag matrix resulting from the weightings on control rate. It can be identified with neuromotor bandwidth limitations and/or pilot reluctancy to make rapid control movements. v_u is an "equivalent" motor noise vector representing imperfect execution of the commanded control inputs. For well-designed manipulators the autocovariance V_{u_i} appears to scale with the control variance $\sigma^2_{u_i}$ according to $V_{u_i} \approx 0.01\, \sigma^2_{u_i}$.

The optimal control model has been validated against experimental data for a variety of control tasks. The predictive capability of the model is extensively demonstrated for single-axis, stationary tracking tasks (see e.g.. Refs. 1, 2, 5, 6, 7, 8, 10). A preliminary attempt to address multivariable (in-flight) control tasks (Ref. 4) has been encouraging although additional in-flight validation would be warranted. Although the model is able to deal with non-stationary tasks with non-random inputs (e.g., Refs. 12 and 13) more experimental support is necessary for this type of tasks.

Most validation studies involved "displayed" information provided by display indicators ("needles"). However, a preliminary attempt has been made to describe the outside world cues (Refs. 11 and 15). Also other modalities than vision can be accounted for in the perceptual model. Motion cues are taken into account in reference 14.

2.2.4 Workload model

Performing the continuous information processing and control task described in the foregoing paragraphs is accompanied by a certain "cost". This "side of the coin" is often the most sensitive (variable) because of the adaptive capabilities of the human operator and therefore an essential aspect of the (reliability of the) man-machine system.

Several psychological notions can be associated with this concept, e.g., attention, effort and workload. One way to deal with such a global, intervening (not directly measurable) psychological concept, is to resort to a specific definition providing a meaningful representation of the pertinent concept.

In this context, human operator "workload" is defined in terms of the foregoing pilot helicopter model. Specifically, the workload model involves two psychological notions: "attention" and "arousal".

In accordance with the usual definitions of workload, attention, as defined before, reflects the fraction of information processing capacity or fraction of time available. This level of attention, P_o, is partly voluntary devoted to the task and partly dictated by the properties of the task (often referred to as "the demand of the task").

Not only this quantitative information processing aspect determines the load imposed on the human operator. Some information is more "arousing" than other. Arousal can be associated with the activity of the central nervous system and is widely assumed to be an important component of human operator workload. This aspect of arousal (or unvoluntary attention in reference 16) is included in the workload model in terms of the sensitivity, S, of task performance (cost functional, J) to the momentary attention paid by the subject.

The workload model represents the components attention (following reference 17) and arousal according to the expression

$$W = S/P_o \ \text{(dB)} \tag{9}$$

with

$$S = \partial J/\partial P_o \ \text{(dB)}$$

where the partial derivative indicates that the other model parameters are kept constant. This model has been shown to correlate excellently with subjective ratings and physiological measurements both in laboratory experiments and in-flight (Refs. 4, 10, 11 and 18).

2.2.5 Monitor and decision making model

The perceptual model combined with the information processing model describes the manner in which the human operator will process the data available to him, y_p, to generate an estimate of the system state, $\hat{x}$, with certain accuracy (indicated by the error covariance Σ). The pair $(\hat{x}, \Sigma)$ constitutes a sufficient statistic for testing hypotheses about x based on the data y_p.

This can be described by the subjective expected utility model (Refs. 5, 6, 19 and 20) which is based on the assumption that the human operator decides (selects between possible hypotheses) to obtain the maximum (expected) profit.

The decision process is characterized by the following stages

- formulate N possible hypotheses, H_j
- asses (posterior) probabilities of all hypotheses based on the available information, y_p, $P(H_j/y_p)$
- determine M possible decisions, D_i
- assign the utilities to each hypothesis/decision combination, U_{ij}
- determine the maximum utility-decision $D_i = D^*$ yielding $E = E_{max}$, where

$$E\{U/D_i\} = \sum_{j=1}^{N} U_{ij}\, P(H_j/y_p) \tag{10}$$

Many decision involve the choice between two hypotheses (e.g., a successful landing or a go-around). In that case the binary decision strategy is given by

$$
\begin{aligned}
D &= D_1 \quad \text{if } U_1 P(H_1/y_p) > U_o P(H_o/y_p) \\
D &= D_o \quad \text{otherwise}
\end{aligned}
\tag{11}
$$

where $U_1 = U_{11} - U_{01}$ and $U_0 = U_{00} - U_{10}$.

For given utilities the model can be used to compute the various measures of decision performance (the probability of wrongly deciding D_0 and D_1 he model is validated for single variable tasks (Ref.5) as wel asks involving multivariable hypotheses (Ref.6). However, these re restricted to stationary (continuous) decision tasks. Intermittent human decision making behavior for rare events (allowing an extrapolation to realistic aircraft situations) requires further model development and experimental validation.

3 EXAMPLES

In this chapter two exemples are presented in order to illustrate how the foregoing theoretical framework can be utilized to study manned aerospace systems.
The first example concerns IFR helicopter control. Results of both a theoretical analysis and an experimental in-flight program are presented in section 3.1
The second example pertains to the use of outside world information in aircraft control. The task considered is a visual manual approach. The analysis is summarized in section 3.2 involving the effect of visibility conditions, Direct Lift Control and a simple Head-up display on the manual approach performance.

3.1 IFR helicopter control tasks

This example is included in this paper to illustrate the potentials of the optimal control model structure to predict and explain the important characteristics of realistic operational helicopter missions. For this, three helicopter instrument control tasks were investigated: a hover task and two navigation tasks at two different heights.

3.1.1 Control tasks

The instrument hover task consisted of stabilizing an Alouette III helicopter at a height of 600 ft with minimal horizontal (ground) speed. The three attitude angles were displayed on a three-axis ADI shown in figure 5. Horizontal velocity components were presented via the cross pointers shown in the figure.
Furthermore, the two navigation tasks consisted of flying along a desired track with an indicated airspeed of 60 kts at a prescribed height of 600 and 150 ft, respectively. Apart from airspeed, all information to perform the task was provided by the ADI. For experimental and modeling details of the tasks the reader is referred to reference 4.

3.1.2 Model and experimental results

Model predictions were obtained on the basis of several assumptions for which the reader is referred to reference 4. The results are given in table 1 for the hover task containing also the experimental results of three subjects. These experimental results indicate that there is a substantial difference in hover performance between the three subjects. The model predictions concerning the guidance variables (height, horizontal velocity) are clearly too optimistic. However, the trend in performance among the subjects leads to the conclusion that the model predictions reflect the "limit" (optimum) of pilot control behavior (of the well-trained, well-motivated pilot).

This conclusion applies also to the results of the high level (600 ft) navigation task shown in table 2. For this task the inter-subject variability is considerably less than for the hover task; therefore, also the average performance is given in table 2.
The experimental results of the low level navigation task are only significantly different from the high level navigation task with respect to the height performance ($RMSh_L/RMSh_H = 0.8$). The model did precisely predict this performance improvement.

It could be concluded from the foregoing results that the optimal control model predictions do reflect optimal control behavior, i.e., the model results represent the best attainable performance (not the average pilot's performance but the best pilot's performance).

An other (diagnostic) use of the model is made when matching the experimental results by varying the key model parameters.
Two key model parameters were varied to match the hover task for two subject which will be presented here for illustrative purposes: the indifference threshold ("region of no control action") and the overall level of attention.
Expecially the first parameter can be related to the motivation of the pilot which appeared to vary substantially between the subjects participating in the present experiment.

The model results are shown in table 3 and compared with the measured scores for both subjects. Generally, there is now an excellent agreement between all important model and measured performance scores, by varying primarily the indifference threshold ratio.
This shows that the model provides a suitable framework to formulate differences in control behavior between pilots, basically in terms of two model parameters: the indifference threshold ratio and the overall level of attention. Both reflect personality traits, such as motivation.

Finally, pilot workload model predictions are compared with subjective ratings and physiological variables. The result is given in table 4. The workload model predicts that the hover task is more demanding than the two, about equally demanding, navigation tasks. This is supported by most experimental measures, also indicating that the hover task is the most demanding and that, on the average, there is no marked difference between the high and low navigation tasks (see bothem table 4).
From this result can be concluded that the workload model results are in good accordance with other indicators of pilot control effort.

3.2 Visual manual approach task

This example is included to illustrate the model capability to describe the use of outside world information. The task considered is a visual manual approach.

3.2.1 Task variables

Two visibility conditions are considered: a good visibility condition (VC1) implying that the complete runway and horizon can be perceived -providing the glidepath deviation (α)- and a restricted visibility condition (VC2) for which no runway end or horizon can be discerned so that vertic . has to be based on the inclination angle (ω) of the runway sides

rurtnermore, the effect of Direct Lift Control (DLC) on the manual approach performance is investigated by comparing a basic configuration (typified by an approximated relationship between flight path angle and pitch attitude $\gamma = \Theta - \dot{\gamma}/Z_w$) and a configuration with DLC implemented such that the vertical damping represented by Z_w is large and therefore $\gamma \doteq \Theta$. Details concerning gust disturbance characteristics, aircraft dynamics, etc. are given in references 11 and 15.

Finally, the potential use of a simple Head-Up Display (HUD) is demonstrated. The HUD consists of a pitch bar which has to coincide with the touch-down "point" (by nulling $\tilde{\Theta} = \Theta - \alpha$). Pilot model parameters are given in reference 11.

3.2.2 Results and discussion

Only the vertical approach performance is considered here in terms of the glidepath deviation (α) at 200 ft in front of the runway*, and the variances of the pitch angle (Θ) and the elevator (δ_e).

The DLC-configurations have been investigated also in the theoretical and experimental program (fixed-based simulation) described in reference 11. The agreement between model performance sores and experimental results which is shown in table 5 indicates that the model accurately describes the visual approach tasks. The corresponding, rather unique set of pilot model parameters (primarily the perceptual thresholds involved and the attention dedicated to the tasks) can be used to reliably predict the effect of the afore-mentioned variables: visibility, DLC and HUD.

In table 6 the predicted approach performance of all selected configurations is summarized. Also the computed (optimal) fractions of attention paid to the available visual cues are given.

The main effect of DLC is a considerable reduction of pitch angle and control activity for both visibility conditions. The variance of the actual approach angle is only slightly reduced (5 % to 10 %). The model analysis reveals that this is due to the fact that for both visibility conditions guidance information is too poor (relatively large perceptual thresholds) to take advantage of the improved aircraft dynamics.

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* It was assumed that the aircraft position was "frozen" at a fixed point of the approach path corresponding with a nominal altitude of 200 ft for a 3^o approach. Thus no range-varying effects were considered.

Interestingly enough, the effect of a HUD providing the difference ($\tilde{\theta}$) between the pitch angle and the approach angle is exactly complementary. Now, considerably superior approach angle information is available. The model predicts that 20 % to 26 % of the time this information will be attended to and the remaining time will be devoted to the approach angle variations ($\dot{\alpha}$). The resulting approach angle performance is improved with 50 % for both visibility conditions.
Combining the improved aircraft dynamics and the superior viewing condition (HUD) yields the expected substantial improvement in overall approach performance. This is only conducted for the good visibility condition (VC1). Now, the improved aircraft dynamics result in an additional approach angle performance improvement of 50 % because, in this case, the viewing conditions allow to take advantage of the superior aircraft handling qualities. The final improvement in the approach angle performance is a factor of 4 (!). Control activity is reduced with about the same factor. Pitch angle deviations are even reduced with a factor of 10.

In summary, the foregoing model analysis illustrates that the study of manned aerospace systems involves the complex interaction of various task-related and pilot-related variables. The pilot-aircraft model has been shown to provide a useful tool to assess quantitatively the effect of important task characteristics.
Specifically, the example shows the effect of the visibility condition on the manual approach performance. Furthermore, the model analysis leads to the favourable combination of DLC and a simple HUD resulting in a substantial improvement of overall approach performance.

4 CONCLUDING REMARKS

The foregoing pilot-helicopter model is based on the funfamental assumption that the well-motivated, well-trained human operator behaves in a near optimal manner subject to his inherent constraints and the extent to which he understands the objectives of the task.

Operationalizing this hypothesis amounts to a specification of criteria for optimality and human limitations by modelling (describing) pilot functioning according to the various stages of information processing. In linear optimization and estimation theoretical terms it is described how the pilot perceives and processes information resulting in an internal representation of the task. This process directly pertains to human monitor behavior.
Based on the information provided by this internal model the pilot controls the helicopter according to an optimal control strategy (yielding a minimal value of the cost functional). This optimal control model has been extensively validated and shown to represent meaningfully continuous information processing and control behavior even of complex in-flight control tasks.
Also pilot decision making is modelled. Based on the information of the same internal model the pilot is assumed to decide (select between possible hypotheses) to obtain the maximum profit. Although this model has been successful in describing stationary, multivariable, binary decision tasks, it will still have to be tested for rare events in order to enhance the fidelity of the model and its predictive capability.

Previous studies and the given examples show that the pilot-helicopter model provides a powerful task analysis tool. It represents a rational, systematic structure of the complex manned aerospace system (e.g., pilot-helicopter system) allowing a straight-forward investigation of a variety of highly interacting task-related and pilot-related characteristcs.

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TABLE 1

Model predictions and experimental results for the hover task

PARAMETER			MODEL PRED.	MEASURED SUBJECT A		
				A	B	C
σ_θ	(pitch attitude)	(deg)	1.6	1.7	1.6	1.4
σ_ϕ	(roll attitude)	(deg)	1.0	1.6	1.3	1.6
RMS ψ	(heading)	(deg)	4.3	2.5	4.8	4.5
RMS h	(height)	(ft)	13.1(16.3)	21.3	55.1	100.4
	velocity)	(kts)	0.8(1.0)	1.5	2.5	2.8
	al velocity)	(kts)	0.4(0.7)	1.2	1.6	2.2
	ontal velocity)	(kts)	0.9(1.2)	1.9	3.0	3.5
σ_{δ_e}	(long. cyclic)	(deg)	1.1	1.1	1.0	0.7
σ_{CP}	(coll. pitch)	(deg)	1.1	1.1	0.8	0.4
σ_{δ_a}	(lateral cyclic)	(deg)	0.2	0.6	0.5	0.6
σ_{δ_r}	(tail rotor pedal)	(deg)	1.7	1.1	0.6	0.7
Overall performance J_m			0.05(0.09)	0.20	0.66	1.49
Replications			-	15	5	3

(.): predictions with thresholds

TABLE 2

Model predictions and experimental results for the high level navigation task

PARAMETER			MODEL PRED.	MEASURED SUBJECT A				AVERAGE
				A	B	C	D	
σ_θ	(pitch attitude)	(deg)	0.9	2.6	1.9	2.2	1.8	2.2
σ_ϕ	(roll attitude)	(deg)	2.8	2.8	2.4	3.1	2.4	2.7
σ_ψ	(heading)	(deg)	3.6	4.9	6.2	6.6	3.6	5.5
RMS h	(height)	(ft)	12.5(15.4)	25.4	41.3	39.3	35.6	35.9
RMS u	(airspeed)	(kts)	0.8(1.4)	5.2	6.5	7.3	7.0	6.6
RMS y	(cross track deviation)	(ft)	38.7(43.2)	43.0	84.5	66.3	76.8	69.4
RMS $\dot{y}$	(cross track rate)	(kts)	4.1	3.7	4.7	4.6	4.0	4.3
σ_{δ_e}	(long. cyclic)	(deg)	0.7	0.8	0.7	0.6	0.5	0.7
σ_{CP}	(coll. pitch)	(deg)	0.9	1.2	1.2	0.5	0.3	0.9
σ_{δ_a}	(lateral cyclic)	(deg)	1.5	0.4	0.4	0.4	0.3	0.4
σ_{δ_r}	(tail rotor pedal)	(deg)	1.2	0.9	1.0	0.6	0.4	0.8
Overall performance, J_m			0.05(0.07)	0.11	0.35	0.26	0.27	0.25
Replications			.	9	7	5	3	24

(.): predictions with thresholds

TABLE 3

Model "match" and experimental results of the hover task

PARAMETER			SUBJECT A		SUBJECT B	
			MODEL	MEASURED	MODEL	MEASURED
σ_θ	(pitch attitude)	(deg)	2.1	1.7	2.1	1.6
σ_ϕ	(roll attitude)	(deg)	1.4	1.6	1.5	1.3
RMS ψ	(heading)	(deg)	6.8	2.5	7.8	4.8
RMS h	(height)	(ft)	22.3	21.3	54.5	55.1
RMS u	(long. velocity)	(kts)	1.5	1.5	2.1	2.5
RMS v	(lateral velocity)	(kts)	1.2	1.2	1.7	1.6
RMS v_h	(horizontal velocity)	(kts)	1.9	1.9	2.7	3.0
σ_{δ_e}	(long. cyclic)	(deg)	1.0	1.1	1.0	1.0
σ_{CP}	(coll. pitch)	(deg)	0.8	1.1	0.8	0.8
σ_{δ_a}	(lateral cyclic)	(deg)	0.2	0.6	0.14	0.5
σ_{δ_r}	(tail rotor pedal)	(deg)	1.6	1.1	1.7	0.6
Overall performance, J_m			0.20	0.20	0.58	0.66
P_0			-16 dB		-15 dB	
Threshold ratio TH			1/6 display limit		1/2 display limit	

TABLE 4

Comparison of control effort model results, subjective ratings and physiological variables

SUBJECT	TASK	COMPUTED WORKLOAD	SUBJECTIVE RATING		PHYSIOLOGICAL VARIABLES					
			EFFORT	DEMAND	Heart rate	RMSSD 1)	log 1) ABP	Resp. freq.	SCL 2)	SRR 3)
A	Hover	17.0	5.0	5.5	85.4	2.0	1.0	17.6	41.5	.26
	Low navigation	15.9	4.5	5.4	71.0	1.9	.9	16.9	41.9	.22
	High navigation	15.9	4.3	4.8	72.1	1.8	.9	16.4	39.4	.25
B	Hover	16.5	7.5	7.4	84.5	2.5	.7	19.5	22.5	.40
	Low navigation	15.1	6.4	6.4	78.8	3.1	.9	19.3	22.1	.32
	High navigation	14.9	6.7	6.7	78.1	3.2	.8	19.2	21.0	.40
Average of 4 subjects	Low navigation	15.0	5.2	5.5	77.7	2.1	.8	18.3	38.1	.22
	High navigation	15.1	5.2	5.7	77.8	2.0	.8	18.0	36.8	.28

1) heart rate variability measure

2) SCL: skin conductance level (average)

3) SCR: skin conductance response (variability)

TABLE 5

Comparison of model and experimental results

CONFIGURATION	PERFORMANCE	σ_{α}^{2} (deg^2)	σ_{θ}^{2} (deg^2)	$\sigma_{\delta_e}^{2}$ (N^2)
VC1/ DLC	measured	0.077	0.054	23.0
	model	0.084	0.062	23.5
VC[illegible] DL[illegible]	measured	0.193	0.098	26.4
	model	0.189	0.095	26.7

TABLE 6

Predicted performance of all model configurations

CONFIGURATION	ATTENTION ALLOCATION f_i	σ_{α}^{2} (deg^2)	σ_{θ}^{2} (deg^2)	$\sigma_{\delta_e}^{2}$ (N^2)
VC1/BASIC	α : 0.6 $\dot{\alpha}$: 0.4	0.095	0.471	74.8
VC1/DLC	α : 0.6 $\dot{\alpha}$: 0.4	0.084	0.062	23.5
VC1/HUD	$\dot{\alpha}$: 0.74 $\tilde{\theta}$: 0.26	0.049	0.423	68.8
VC1/DLC/HUD	$\dot{\alpha}$: 0.85 $\tilde{\theta}$: 0.15	0.022	0.045	21.7
VC2/BASIC	ω : 0.55 $\dot{\alpha}$: 0.45	0.198	0.535	84.6
VC2/DLC	ω : 0.55 $\dot{\alpha}$: 0.45	0.189	0.095	26.7
VC2/HUD	$\dot{\alpha}$: 0.8 $\tilde{\theta}$: 0.2	0.094	0.517	81.7

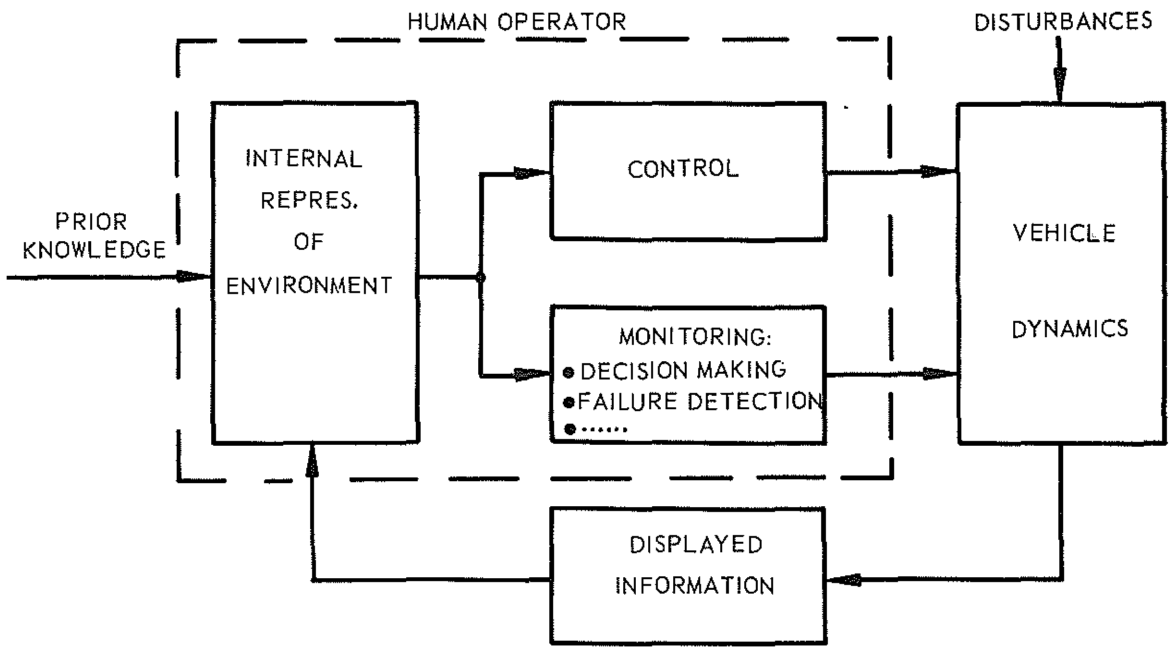

Fig. 1 Block diagram man-machine system

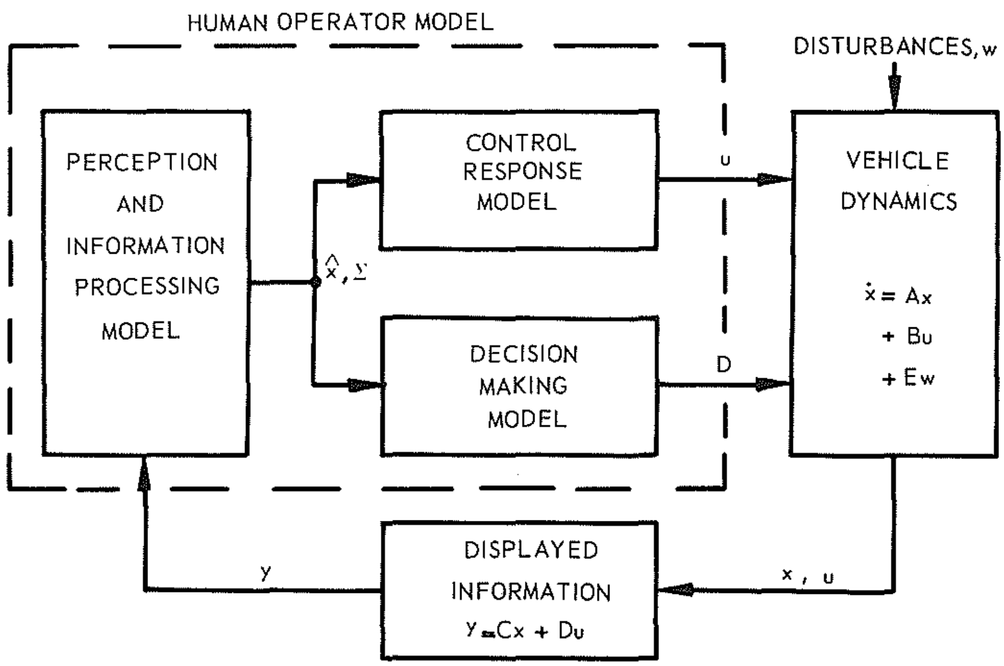

Fig. 2 Man-machine model

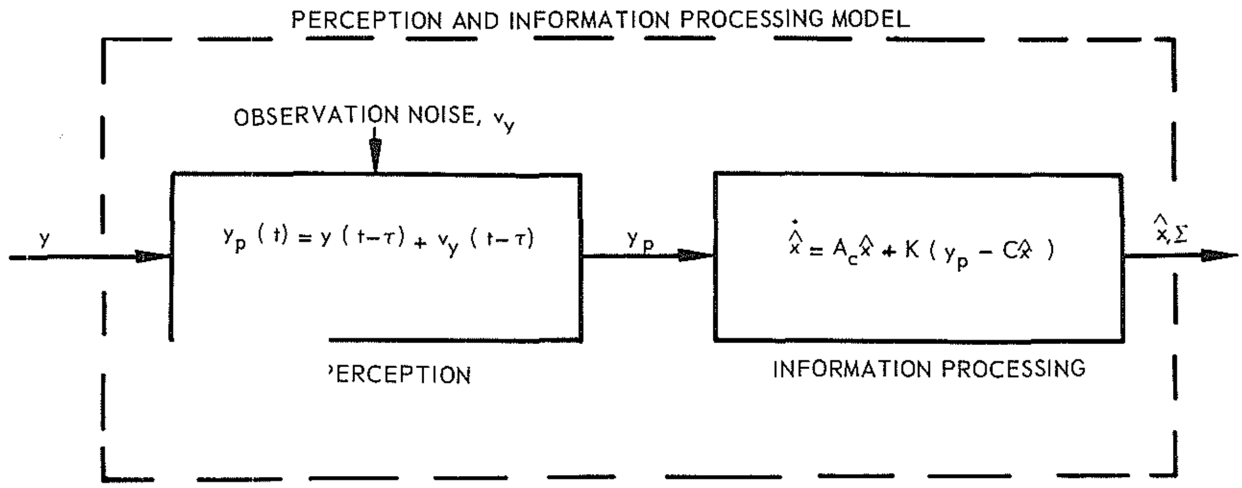

Fig. 3 Perception and information processing model

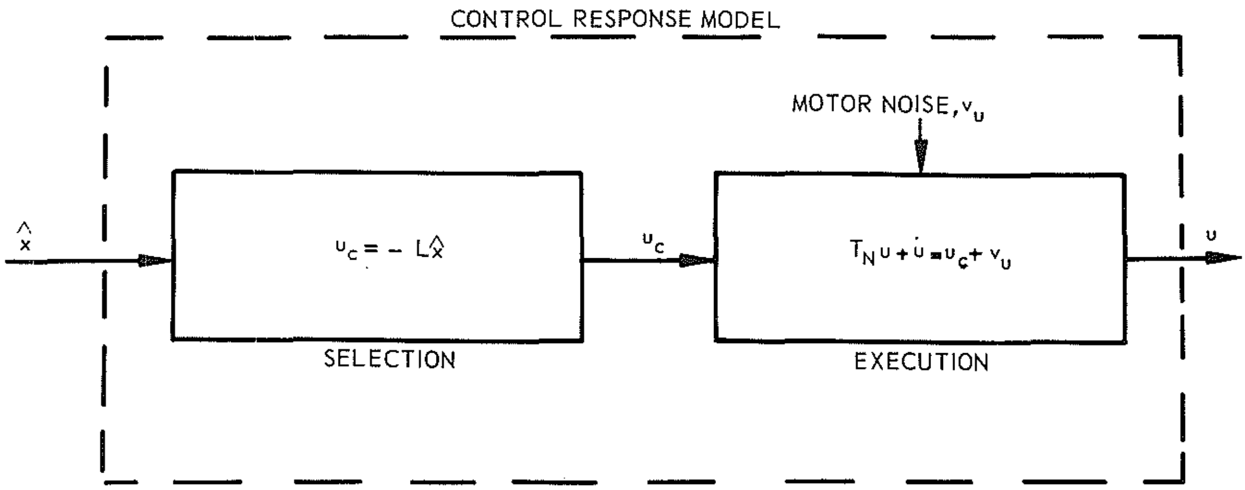

Fig. 4 Control response model

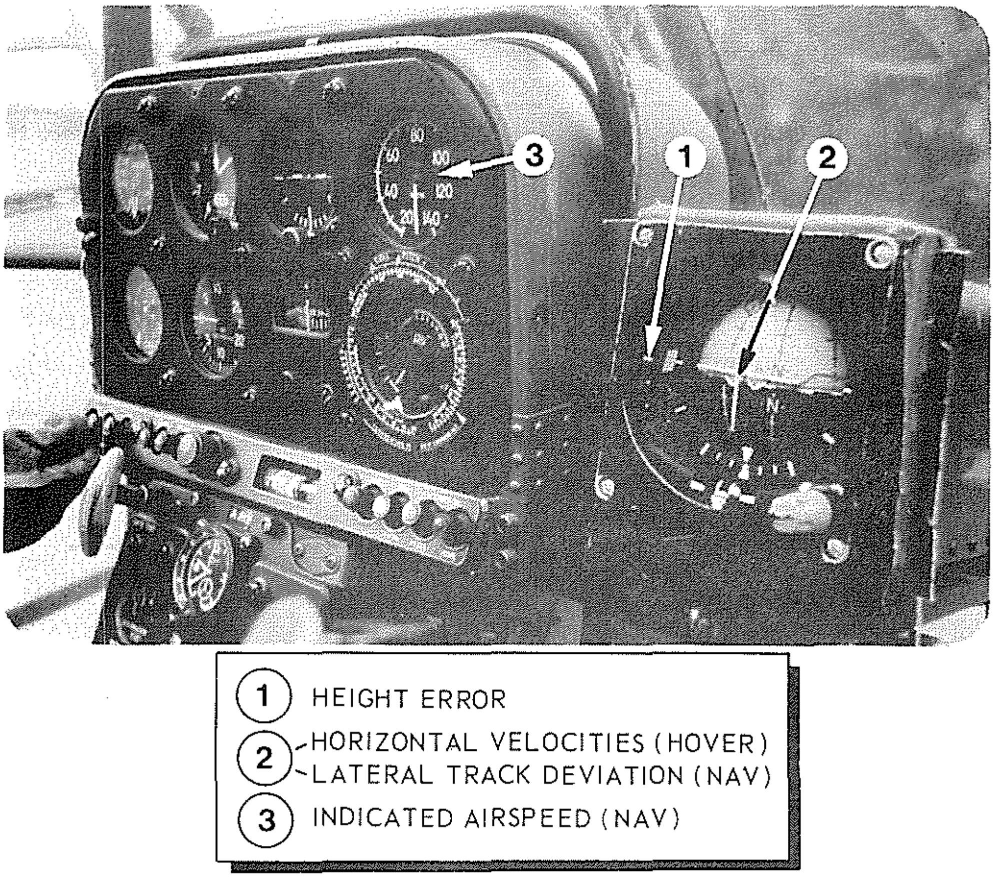

Fig. 5 Alouette III flight instruments

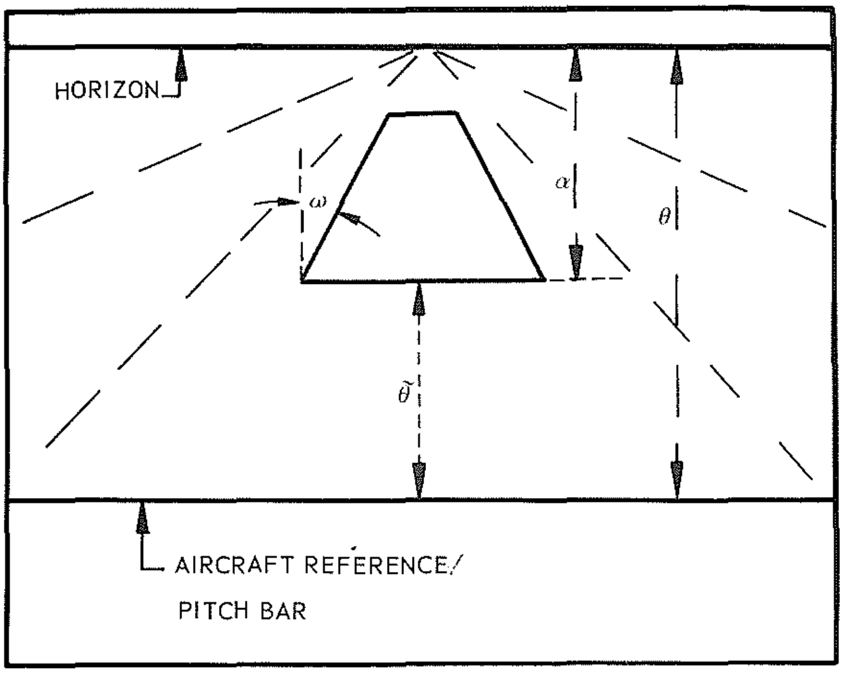

Fig. 6 Visual approach scene characteristics