N79-17477

THE EFFECTS OF DEVIATE INTERNAL REPRESENTATIONS IN THE OPTIMAL MODEL OF THE HUMAN OPERATOR

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May 1977

1. Introduction

Modern control and estimation theory have been used successfully to develop a model for human performance in continuous control tasks [1]. This model, frequently referred to as the optimal control model of the human operator, has been validated extensively by experimental data and has been applied to a variety of problems. The model incorporates an "internal model" that is an exact replica of the system model as part of a Kalman filter sub-model that represents human information processing. The concept that the human operator builds an internal model of his "universe" (e.g., through training) is not uncommon in psychology. Moreover, the assumption of a perfect internal model appears to be a satisfactory one in many instances, as has been demonstrated by the agreement between model predictions and experimental data.

There are situations, however, in which the assumption of a perfect model does not appear suitable and important applications which would benefit from allowing for an internal model that is different from the system model. For example, naive or untrained trackers may not have "perfect" models even for simpler systems. Tracking of targets executing deterministic but unknown motions requires admitting imperfect internal models (for the input) for complete generality. When a system failure occurs there is a change in the system; until this change is detected and the failed system identified the operator's model is different than the system model.

In this note, some of the issues and equations involved in predicting closed-loop man-machine performance for situations in which the human operators' knowledge of the system and/or environment are imperfect are presented and discussed. Several examples to illustrate some of the effects to be expected when such is the case are then given. Details concerning equation development may be found in [2].

2. Equations for Deviate Internal Model

Let the system to be controlled by the human operator be described by the linear equations

$$\dot{\underline{x}}(t) = \underline{A}\,\underline{x}(t) + \underline{B}\,\underline{u}(t) + \underline{E}\,\underline{w}(t) \quad (1)$$

$$\underline{y}(t) = \underline{C}\,\underline{x}(t) + \underline{D}\,\underline{u}(t) \quad (2)$$

where $\underline{x}$ is an n_x dimensional vector of system state variables, $\underline{u}$ is an n_u-dimensional vector of control inputs, $\underline{y}$ is an n_y-dimensional vector of displayed outputs and $\underline{w}$ is an n_w-dimensional vector of a zero-mean, gaussian, white nose process with auto-covariance $E\{\underline{w}(t_1)\underline{w}'(t_2)\} = \underline{W}\,\delta(t_1-t_2)$. We assume $\underline{w}(t)$ is stationary so that $\underline{W}$ is constant for all t. We will also assume that the matrices in (1) and (2) are constant. Thus, we treat a time-invariant system. Moreover, we will be concerned here only with the steady-state solution.

The optimal control model for the human operator has the structure illustrated in Figure 1. The structure and equations of Figure 1 have been documented in [1]. The blocks in Figure 1 labeled estimator and predictor model human information processing. For these processes to be performed "optimally" it is necessary to have perfect knowledge of the system ($\underline{A}$, $\underline{B}$, $\underline{C}$, $\underline{D}$, $\underline{E}$), the driving noise-statistics ($\underline{W}$), and the parameters describing human limitations (τ, $\underline{T}_n$, $\underline{V}_y$, $\underline{V}_n$). The control gains, $\underline{L}^*$, model human control-command generation or compensation and are selected so as to minimize a quadratic cost functional. To achieve a minimum, i.e., to compute $\underline{L}^*$, it is necessary to know $\underline{A}$, $\underline{B}$ and the weighting coefficients $(q(\cdot)_i)$. Thus, there are three classes of quantities or parameters (system/enviroment, own limitations, and cost weightings) that are required to be known by the human operator if he is to perform optimally.

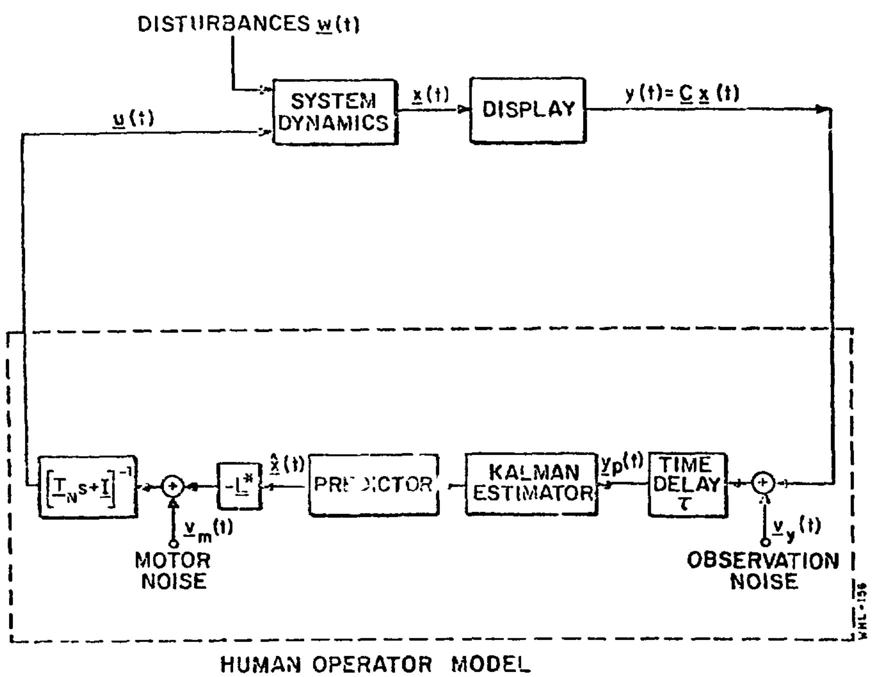

Figure 1. Structure of the Optimal Control Model

There are many assumptions that can be made concerning the human operator's knowledge of the requisite information. At one extreme, one can assume that all quantities are unknown (including the dimensions of the various matrices). At the other end of the spectrum, one can assume that all quantities are known and the human performs optimally. This latter assumption is, of course the one used in formulating the optimal control model; for trained operators, it seems closer to the truth (or, at least it explains the data better) that the assumption of complete ignorance. Here, for reasons discussed in [2], we assume the human operator knows the cost functional weightings and his own limitations of delay, neuromotor-lag and observation noise. On the other hand, we allow the system matrices to be unknown (even as to dimension) and the motor-noise also to be unknown.

To implement the above assumptions, we assume the human operator's internal model to be

$$\dot{\underline{z}}(t) = \tilde{\underline{A}}_1 \underline{z}(t) + \tilde{\underline{B}}_1 \underline{u}_c(t) + \tilde{\underline{E}}_1 \tilde{\underline{w}}_1(t) \qquad (3)$$

$$\underline{y}(t) = \tilde{\underline{C}}_1 \underline{z}(t) \qquad (4)$$

$$E\{\tilde{\underline{w}}_1(t_1)\, \tilde{\underline{w}}_1'(t_2)\} = \tilde{\underline{W}}_1\, \delta(t_1-t_2) \qquad (5)$$

where

$$\tilde{\underline{A}}_1 = \begin{bmatrix} \tilde{\underline{A}} & \tilde{\underline{B}} \\ 0 & -\underline{T}_N \end{bmatrix}, \quad \tilde{\underline{B}}_1 = \begin{bmatrix} 0 \\ \underline{T}_N^{-1} \end{bmatrix}, \quad \underline{C}_1' = \begin{bmatrix} \underline{C}' \\ \underline{D}' \end{bmatrix}$$

$$\tilde{\underline{E}}_1 = \begin{bmatrix} \tilde{\underline{E}} & 0 \\ 0 & \underline{T}_N^{-1} \end{bmatrix} \quad \underline{W}_1 = \begin{bmatrix} \tilde{\underline{W}} & 0 \\ 0 & \tilde{\underline{V}}_m \end{bmatrix} \qquad (6)$$

where the matrices with "tildes" indicate internal matrices and Equations (1) and (2) have been "augmented" to incorporate the "neuromotor" dynamics (see Fig. 1 and [1]). The perceived variables remain unchanged inasmuch as the "true" $\underline{y}$ is displayed to the operator. The "internal state" $\underline{z}$ does not have to be of the same dimension as $\underline{x}$. However, we assume that $\underline{y}$ and $\underline{u}$ in the internal model have the same dimensions as the corresponding vectors of the system.

It is now assumed that the human will perform "optimally" for his internal system. These assumptions lead to a set of coupled delay-differential equations. In the special case, where $\underline{x}_J = \underline{Z}$ and $\tilde{C}_1 = C_1$, the following equations describing closed-loop performance are obtained [2]

$$
\begin{aligned}
\dot{\underline{e}}(t) &= (\tilde{A}_1 - \tilde{K}\, C_1)\, \underline{e}(t) + (A_1 - \tilde{A}_1)\, \underline{x}(t-\tau) \\
&\quad + E_1\, \underline{w}(t-\tau) - \tilde{K}\, \underline{v}_y(t-\tau) \\
\dot{\hat{\underline{x}}}(t) &= (\tilde{A}_1 - B_1\, \tilde{L})\, \hat{\underline{x}}(t) + e^{\tilde{A}_1 \tau}\, \tilde{K} \\
&\quad [C_1\, \underline{e}(t) + \underline{v}_y(t-\tau)] \qquad (7) \\
\dot{\underline{x}}_1(t) &= A_1\, \underline{x}_1(t) - B_1\, \tilde{L}\, \hat{\underline{x}}(t) + E_1\, \underline{w}(t) \quad .
\end{aligned}
$$

where e(t) is the state estimation error and $\tilde{K}$ is the Kalman gain for the system described by Equations (3)-(6). Equation (7) is also a "coupled" set of delay-differential equations. Note, however, that if $\tilde{A}_1 = A_1$ the equation for the error "decouples" from the state equation and the estimation equation. Moreover, the system reduces to a set of ordinary differential equations. Performance computations are thereby simplified enormously requiring evaluation of $n_x \times n_x$ matrices only. This is the case even if $\underline{\tilde{W}}_1 \neq \underline{W}_1$. Unfortunately, the assumptions required to achieve this simplification are too stringent for most considerations.

The delay-differential character of the above equations can be circumvented by approximating the human's delay via a Padé approximation. The delay is then considered part of the system dynamics (except for computation of human describing functions); it is a part that is assumed known to the human operator so there will be some compensation for the delay. The resulting closed-loop equations are linear and time invariant. However, their stability is not automatically guaranteed as in the case when all matrices are known to the operator; instead, stability depends on the particular internal model selected. The necessary modifications are given in [2].

3. Examples

Incorrect Knowledge of Vehicle Dynamics

In order to control a vehicle, the pilot must learn its basic response characteristics. One can readily envision this as a two-stage process: 1) the development of an appropriate structural model for the plant; and 2) the adjustment (or fine tuning) of the parameters in that structure. Such a process is consistent with the notions of system identification theory. With regard to structure, the problem in a multi-input, multi-output plant involves learning the couplings as well as the basic modes of response. For single-input, single-output situations a fundamental issue is the order of the plant dynamics, i.e., how many integrations are there between control input and plant output.

Figures 2 and 3 show the predicted describing function and remnant for an operator optimizing his performance based on different internal models of the vehicle dynamics. In each case, the input disturbance was filtered white noise with a 2 rad/sec bandwidth. In Figure 2, the true plant dynamics are K/s, i.e., the rate-of-change of plant output is proportional to the control input. Three curves are shown: one in which the operator has the correct model, one in which the internal model is incorrect (the output is proportional to the input), and one in which the operator has a large pseudomotor noise [2]. The curve corresponding to having the correct model agrees quite well with the measured describing functions for this case [1]. Note that the effect of having the wrong internal model is substantial whereas the effect of high pseudo motor-noise is slight (a reduction in gain at low frequencies.

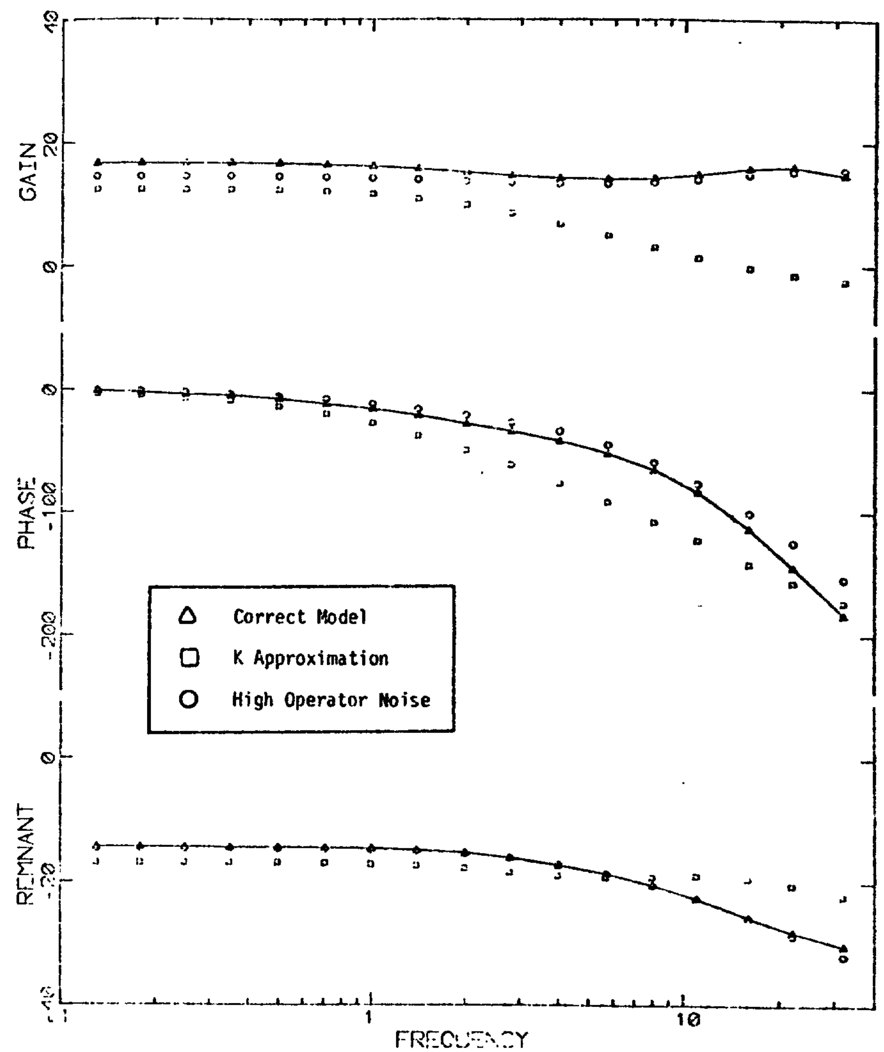

Figure 2. Effects of Deviate Internal Model and High Operator Noise on K/s Regulation

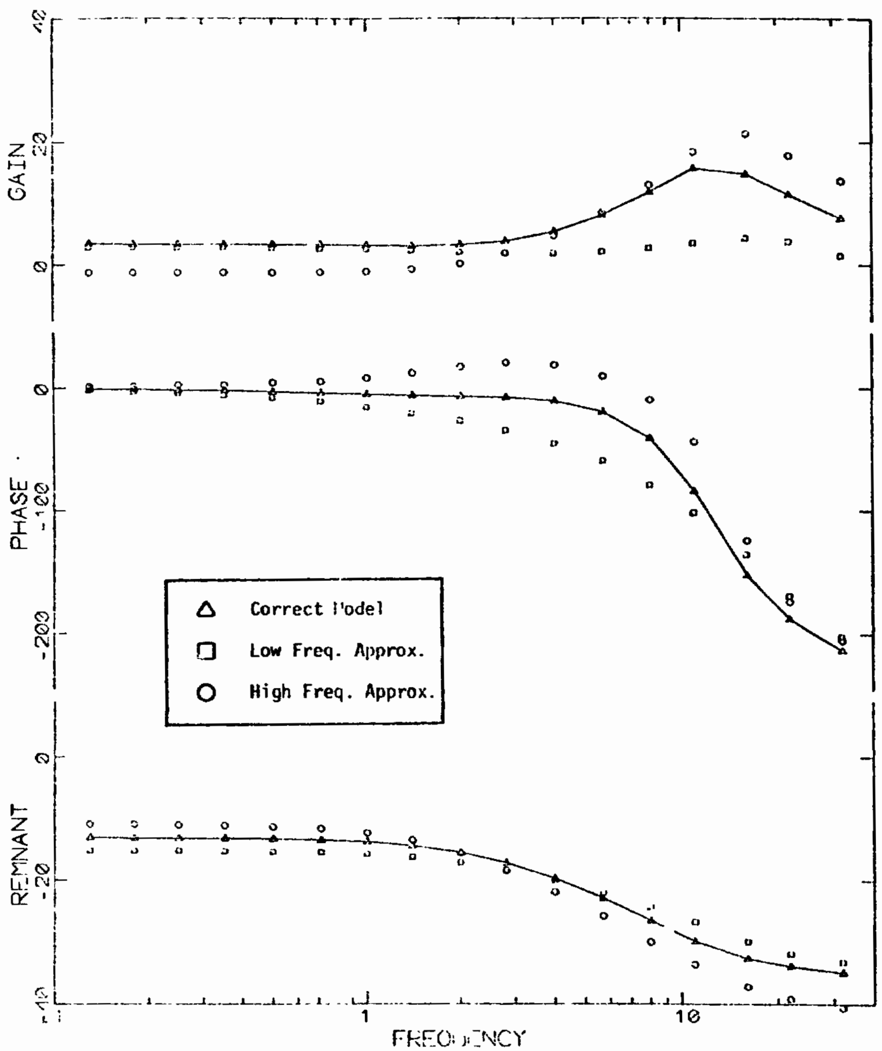

Figure 3. Effect of Deviate Internal Model on Regulation of Roll Disturbance

Figure 3 presents similar results for a more complex plant which represents the roll-synamics of an aircraft. Results are shown for the case in which the operator has the correct internal model and for the cases where the model is a good approximation to either the low frequency or high frequency plant response. Frequency characteristics of the three vehicle models are plotted in Figure 4. Again the results show that we can expect measurements of the pilot's describing functions to be significantly different if operating with different internal models. In this case, the remnant is somewhat less revealing.

Model results were also obtained for the case where the pilot's internal model of the aircraft roll dynamics differed only slightly from the actual dynamics over the entire frequency range of interest. In this case (not shown), differences in the above measurements were not distinguishable from those that might be due to othe parameter changes.

On the basis of these preliminary results, we believe that major structural errors in the operator's internal model of the plant dynamics can be inferred by comparing the measured describing function and remnant with that predicted, by the OCM, for a trained operator. Moreover, the form of the operator's internal model may also be deduced using the OCM. Major parameter errors are also probably discernible. However, the fine-tuning process of model identification may not be distinguished readily from other factors such as general noise-reduction.

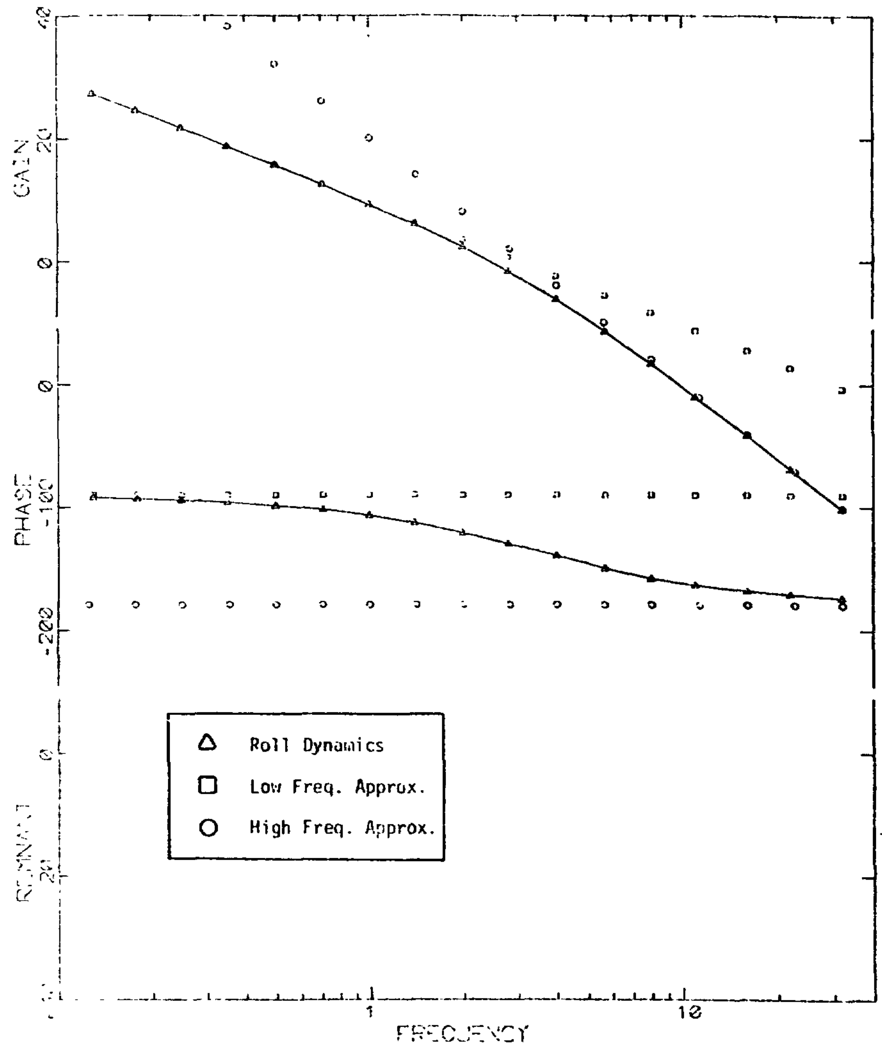

Figure 4. Vehicle Dynamics Approximations for High Performance Roll Dynamics

Learning the Input Characteristics

The K/s example described above was also examined to see if the effects of incorrect knowledge of the input characteristics would be evident. Figure 5 gives results for the case in which the operator overestimates the input bandwidth by a factor of 2. It can be seen that these results differ significantly from the situation in which the input bandwidth is known correctly only in terms of low frequency gain. If we refer to Figre 2, we see that the effect is also different from that of having an incorrect model of the vehicle dynamics.

Perceptual Efficiency

A major application of the wrong internal model concept would be to the study of learning of control strategies. In addition to learning the plant dynamics, it is believed that skill development involves learning to use the available cues most efficiently. We can envision this as a process of proper cue selection as well as noise reduction. For example, the progression-regression hypothesis [3] suggests an increasing utilization of derivative information with learning. It is therefore of interest to compare the effects of inefficient cue utilization and an incorrect internal model. Figure 6 compares predicted describing functions and remnant for optimized performance with and without rate information. The results are for the roll dynamics described earlier and it is assumed that the operator has learned the plant dynamics. It can be seen that failure to utilize rate information has a distinct impact on the measures of control strategy and perceptual efficiency. Most of this impact is at high frequencies, as expected. Furthermore, comparison with Figure 3 reveals that lack of rate information produces a decidedly different result from that obtained with a low frequency approximation to the vehicle dynamics. Thus, it should be

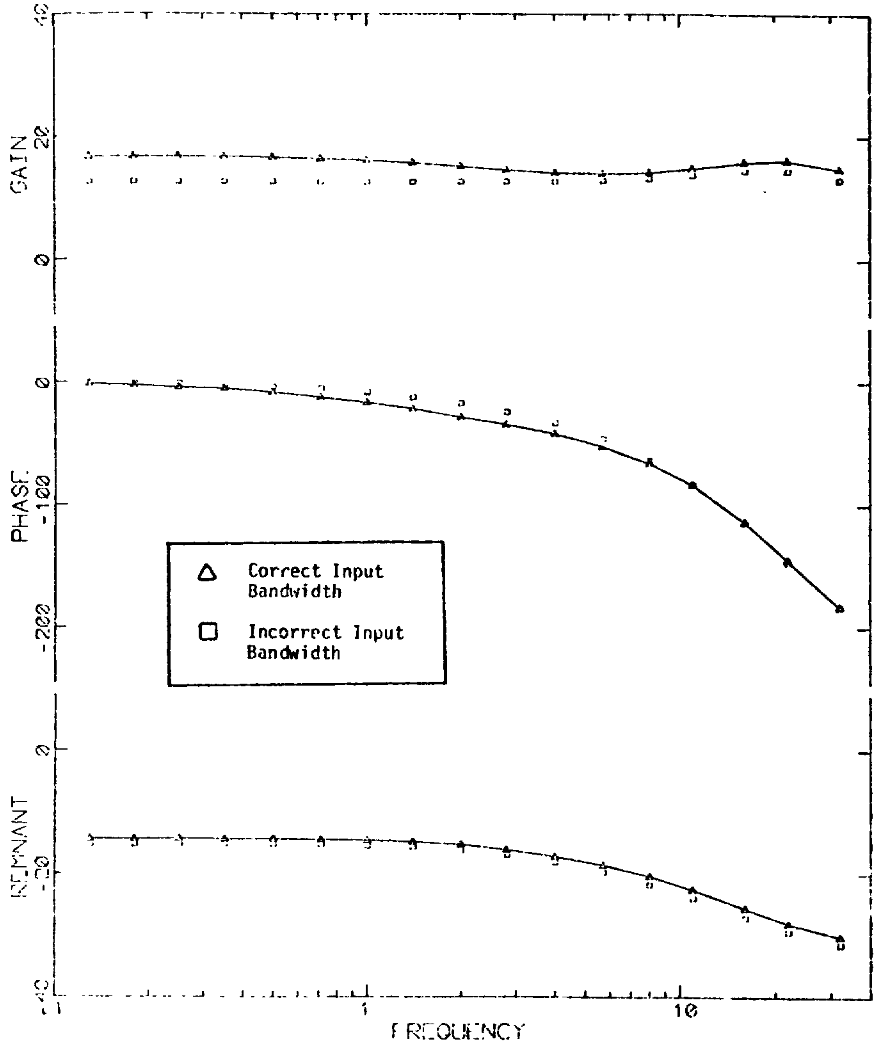

Figure 5. Effect of Wrong Estimate of Input Bandwidth on K/s Regulation

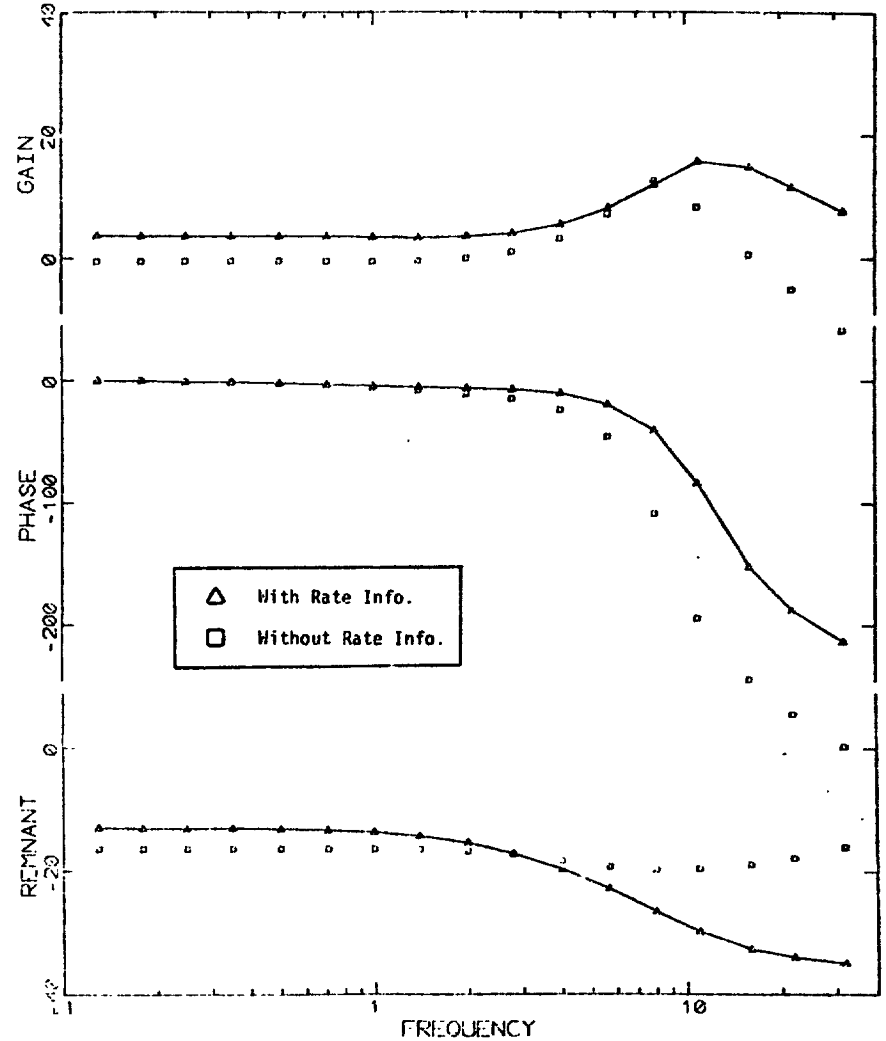

Figure 6. Effect of Non-Utilization of Rate Information on Roll Regulation

possible to differentiate between learning vehicle dynamics and learning to use the available cues from these measures of operator performance.

4. Conclusion

In conclusion, we wish to point out that, while the notion of a deviate internal model is appealing intuitively, in the authors' opinion, its use for trained operators even in complex tasks should be considered with caution for the following reasons: (1) the assumption of a perfect model works quite well for trained operators performing well defined tasks; (2) the observation and motor noises included in the optimal control model already account for some model imperfections; (3) when there is significant process noise, state prediction and estimation is difficult and the contribution to performance degradation of deviate internal models is likely to be reduced significantly; (4) computational requirements for predicting closed loop performance may well increase under this assumption; and (5) most importantly, in order to avoid having to choose among an infinity of possible internal models, rules for picking a specific internal model are needed, and, presently, no such rules exist. On the other hand, the programs developed here and the insights provided by the sensitivity analyses should prove very useful in studying and analyzing the performance of untrained operators.

5. References

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