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A STUDY OF THE EFFECT OF FORCING FUNCTION CHARACTERISTICS ON HUMAN OPERATOR DYNAMICS IN MANUAL CONTROL

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SUMMARY

This paper deals with the effect of the spectrum of the forcing function on the human pilot dynamics in manual control. A simple compensatory tracking experiment was conducted, where the controlled element was of a second-order dynamics and the forcing function was a random noise having a dominant frequency. The dominant frequency and the power of the forcing function were two variable parameters during our experiment.

The results show that the human pilot describing functions are dependent not only on the dynamics of the controlled element, but also on the characteristics of the forcing function. This suggests that the human pilot behavior should be expressed by the transfer function taking into consideration his ability to sense and predict the forcing function.

SYMBOLS

$A_{ij}(k)$	element of k-th autoregressive coefficient matrix
B	backward shift operator
c(t), c(n)	human pilot output
dB	decibel
e(t), e(n)	displayed error
i(t), i(n)	forcing function
K_f	static gain of forcing function filter

M	order of autoregressive model
$m(t)$, $m(n)$	controlled element output
s	variable of Laplace transform
$Y_c(j\omega)$	controlled element
$Y_f(j\omega)$	forcing function filter
$Y_p(j\omega)$	human pilot describing function
Δ	sampling interval
ζ_f	damping of forcing function filter
ζ_n	damping of controlled element
σ_i^2	power of forcing function
ω_f	undamped natural frequency of forcing function
ω_n	undamped natural frequency of controlled element

INTRODUCTION

It is well known that when a human pilot controls the system, his control behavior depends on the characteristics of the forcing function to the system as well as of the controlled element itself. A great number of papers have been published on this problem.

Concerning the effect of the characteristics of the controlled element on pilot behavior, Washizu and Miyajima (reference 1), and Goto and Washizu (reference 2) pointed out in a series of study on manual control of a second-order system that the human pilot takes notice of the periodicity in the response of the controlled element, if any, and makes use of it to improve his control performance.

On the other hand, concerning the effect of the forcing function on pilot behavior, McRuer and Krendel (reference 3) pointed out that as the bandwidth of the forcing function increases, the effective time delay reduces probably due to the muscular reaction characteristics of the human pilot.

The purpose of the present paper is to investigate the effect of the forcing function spectrum on the human pilot dynamics in manual control. A simple compensatory tracking experiment was conducted, where the controlled element was of the second-order dynamics and the forcing function was a random noise having a dominant frequency. The dominant frequency and the power of the forcing function were two variable parameters during the experiment. Pilot describing functions were derived from the autoregressive model coefficients identified using the Akaike's Final Prediction Error method.

EXPERIMENT

The system of our experiment was built up with an analogue computer, an oscilloscope and a control stick with a restoring spring. Its block diagram is as shown in figure 1. The error $e(t)$ was displayed on the oscilloscope by a line segment moving vertically. The pilot was requested to minimize the error to the best of his ability. The controlled element had a second-order stable dynamics, and its transfer function was of the form;

$$Y_c(s) = \frac{\omega_n^2}{s^2+2\zeta_n\omega_n s+\omega_n^2} \quad . \tag{1}$$

The damping ζ_n and undamped natural frequency ω_n of the controlled element were held fixed throughout our experiment such as,

$$\zeta_n = 0.1 \quad ,$$
$$\omega_n = \sqrt{20} = 4.47 \text{ (rad/sec)} \quad .$$

The shaping filter of the forcing function also had a second-order stable dynamics as,

$$Y_f(s) = \frac{K_f\omega_f^2}{s^2+2\zeta_f\omega_f s+\omega_f^2} \quad , \tag{2}$$

where the damping ζ_f was held fixed to 0.1 and the static gain K_f and the undamped natural frequency ω_f were two variable parameters. Thus, the white noise was transformed into a forcing function having a dominant frequency after passing the filter. The dominant frequency was varied by selecting the values of ω_f as,

$$\omega_f = 3.16,\ 2.24,\ 1.58 \text{ (rad/sec)} \quad .$$

We chose four levels for the power of the forcing function σ_i^2 by adjusting K_f of the equation,

$$\sigma_i^2 = \frac{\omega_f K_f^2}{4 \zeta_f} \sigma_w^2 \qquad (3)$$

where σ_w^2 is the power of the noise source.

The experiment was of 12 cases, namely 3 kinds of frequencies and 4 power levels of the forcing function, and two runs of each case were performed. After sufficient excercise, the analog data of the length of 90 seconds for each runs were recorded. The data, i(t), e(t), c(t) and m(t) in figure 1 were transformed into digital data by use of the NOVA mini-computer system. The FACOM 230-75 computer was employed for numerical calculations of the following time series analysis.

ANALYSIS

By the use of the experimental data thus obtained, the human pilot describing functions were identified utilizing a time domain technique; that is, an autoregressive model was fitted to the data by using the Akaike's MFPE (Multiple Final Prediction Error) method. (reference 4)

In the first place, the data were sampled from the analog data of the pilot output c(t) and the error e(t) with the sampling interval Δ, which was set as 0.1 sec. The sampled data are denoted by c(n) and e(n). Then, the autoregressive model of the form;

$$\begin{bmatrix} c(n) \\ e(n) \end{bmatrix} = \begin{bmatrix} A_{11}(B) & A_{12}(B) \\ A_{21}(B) & A_{22}(B) \end{bmatrix} \begin{bmatrix} c(n) \\ e(n) \end{bmatrix} + \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{bmatrix} \begin{bmatrix} \xi_1(n) \\ \xi_2(n) \end{bmatrix} \qquad (4)$$

$$A_{ij}(B) = a_{ij}(1)B + a_{ij}(2)B^2 + \cdots\cdots + a_{ij}(M)B^M \qquad (5)$$

$$Bx(n) = x(n-1) \qquad (6)$$

was fitted to the given data. B is the backward shift operator as shown in equation (6), and $A_{ij}(B)$'s in equation (4) are the power series in B that are made up of the autoregressive model coefficients $a_{ij}(k)$ with k going from 1 through M. The order of the model M is determined by the MFPE method. $\xi_i(n)$'s in equation (4) are mutually independent white noises.

Once we have succeeded in fitting the model to the given data, namely, $\sigma_{12} = \sigma_{21} \fallingdotseq 0$, we can compute the pilot describing function using

$$\hat{Y}_p(j\omega) = \frac{A_{12}(j\omega)}{1 - A_{11}(j\omega)} \quad , \qquad (7)$$

where $A_{11}(j\omega)$ and $A_{12}(j\omega)$ are obtained from $A_{11}(B)$ and $A_{12}(B)$ in equation (4) respectively, by replacing B with $\exp(-j\omega\Delta)$.

This method has recently been put into practical use, and our experience in using it has proved that it is quite efficient and powerful (reference 5). Application of this method to our data was also successful, as the estimated correlation coefficient of the noise sources, $\sigma_{12}/\sqrt{\sigma_{11}\sigma_{22}}$, was quite small.

RESULTS

Figures 2 and 3 are examples of the time histories of the records. Note that in figure 2, namely when the frequency of the forcing function ω_f was large, it is not evident that c(t) was affected by the forcing function periodicity. The pilot seemed to suppress only the controlled element periodicity.

On the other hand, figure 3 shows the time history of the case when ω_f was relatively small. In this case, it is evident that c(t) was made up of two main sinusoidals; one reflected the forcing function periodicity and the other reflected the pilot behavior which seemed to suppress the controlled element periodicity. This suggests that, when ω_f was relatively small, the human pilot behavior was affected by the forcing function.

Above tendencies can be seen more obviously in the power spectrum densities of the pilot output as shown in figure 4; namely in the vicinty of $\omega = \omega_f$, the power spectra were pulled up as σ_i^2 increased, and this phenomenon became more conspicuous when ω_f was relatively small.

Typical pilot describing functions are shown in figures 5 and 6. From these figures, the following tendencies have been observed;

1) If the power of the forcing function σ_i^2 is increased, while keeping the undamped natural frequency ω_f unchanged, the gain of the pilot describing function increases, but the phase lead becomes smaller in the frequency region below the undamped natural frequency of the controlled element ω_n.

2) If the frequency of the forcing function ω_f is decreased, while keeping the power σ_i^2 unchanged, the gain of the pilot describing function increases, but the phase lead becomes smaller in the low frequency range, especially in the neighbourhood of the undamped natural frequency of the forcing function.

Figure 7 shows the performance of the pilot control indicated by σ_e^2/σ_i^2. It is evident that the smaller the undamped natural frequency ω_f was, the better the performance became. This implies that when ω_f was small, the pilot could easily recongnize the forcing function periodicity, and his task becamc easier.

These results lead to the following consideration concerning the forcing function effects on human pilot control behavior.

The effect of the forcing function bandwidth on the pilot describing function is reported in reference 3. It is pointed out in the report that the effective time delay of the human pilot decreases as the bandwidth of the forcing function increases.

On the other hand, the present study put emphasis on the effect of the frequency ω_f and K_f of the forcing function shaping filter. It has been suggested that the increase in the power of the forcing function is likely to work so as to make the pilot employ the control that takes into account the dominant periodicity in the forcing function. The attempt to suppress the dominant frequency component may lead to the reduction of the power of the error. It has also been suggested from the present study that if the response of the controlled element and the forcing function have periodicities, the human pilot would try to augment the system stability by making use of the periodicity in the response of the controlled element, and then, try to make the performance as good as possible by making use of the periodicity of the forcing function. Especially, if the power of the forcing function is large and the two natural frequencies are separated, it would be easy for the pilot to notice these frequencies and to make use of these frequencies in the control.

The present study has shown that the human pilot dascribing functions are dependent not only on the natural frequency of the controlled element, but also on the frequency and the power of the forcing function. These results seem to suggest that the human pilot control behavior couldn't be expressed by a simple transfer function compensating the controlled element delay only, but should be expressed by the transfer function taking into consideration his ability to sense and predict the forcing function.

CONCLUDING REMARKS

The results show the effects of the forcing function on the human pilot such as;

1) If the power of the forcing function σ_i^2 increases, the gain of the human describing function $|\hat{Y}_p|$ increases, but the phase lead of $\hat{Y}_p$ becomes smaller at $\omega < \omega_n$.
2) If the undamped natural frequency of the forcing function ω_f decreases, the gain $|\hat{Y}_p|$ increases but the phase lead of $\hat{Y}_p$ becomes smaller especially in the vicinity of $\omega = \omega_f$.

3) The human pilot seems to try to augment the system stability and make the performance better by use of ω_n and ω_f, especially when σ_i^2 is large, and ω_n and ω_f are separated.

ACKNOWLEDGEMENT

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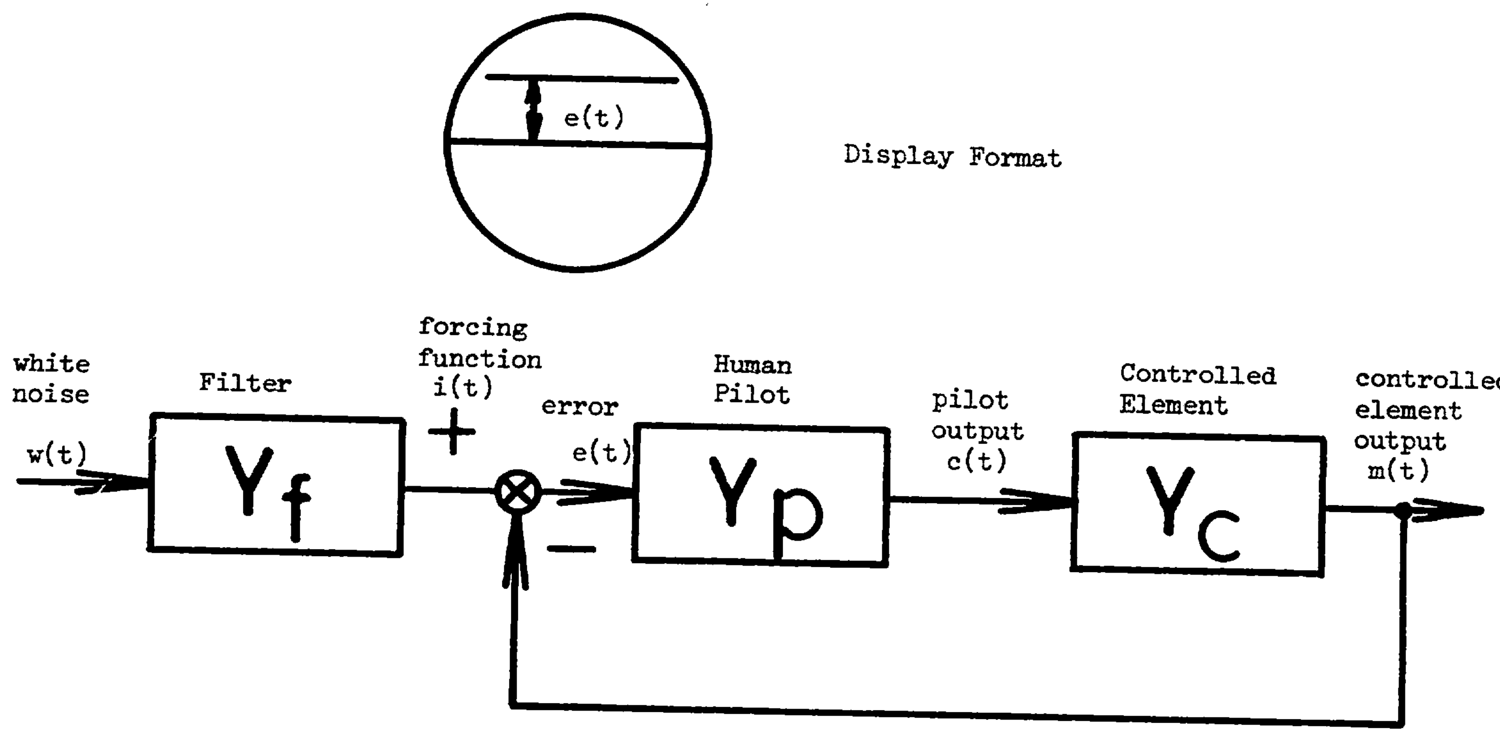
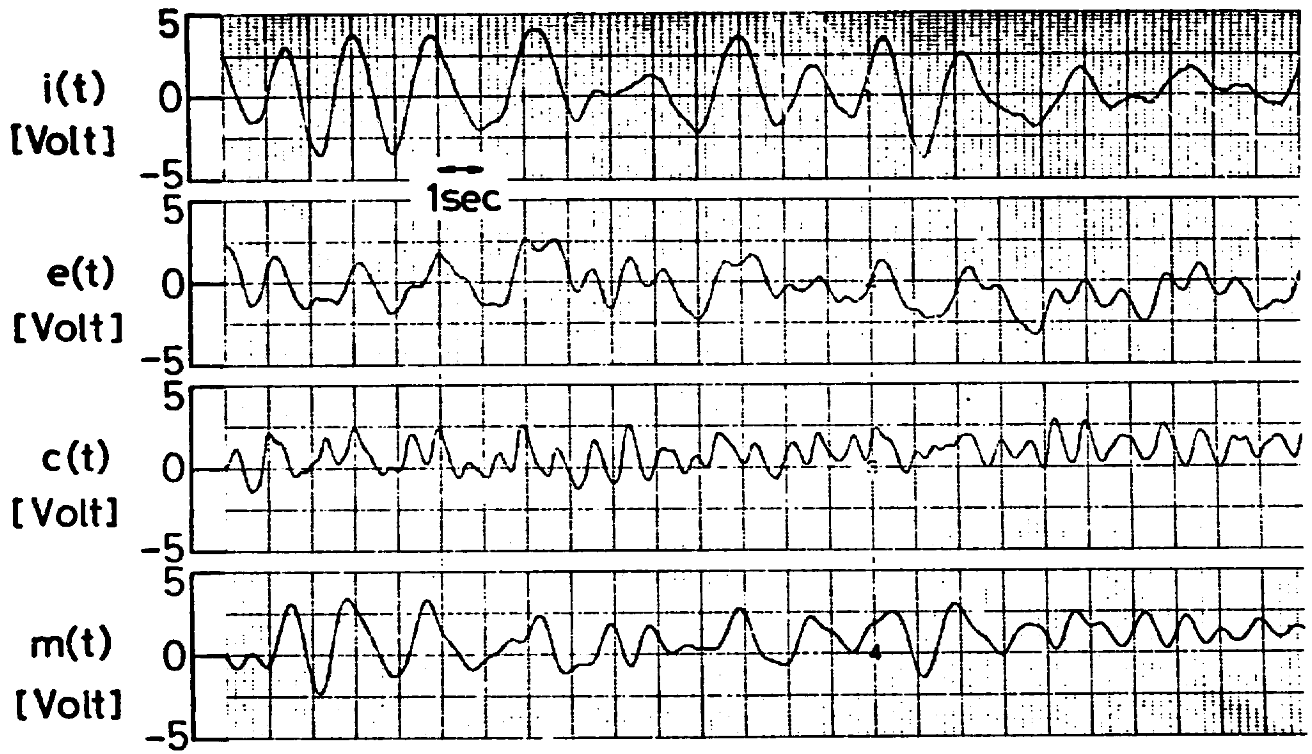
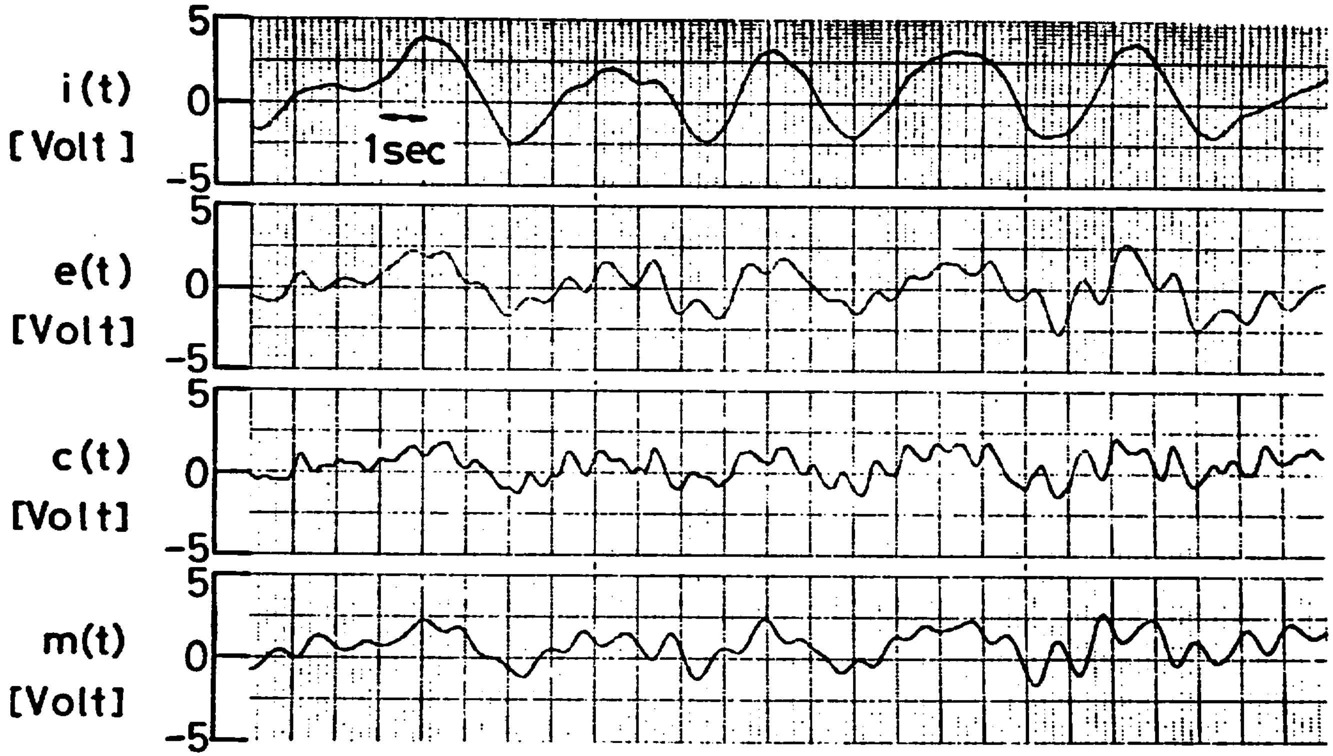


Figure 1. Block Diagram of the Experiment



Forcing Function Periodic Time = $2\pi/\omega_f$ = 1.99 sec.
Controlled Element Periodic Time = $2\pi/\omega_n$=1.40 sec.

Figure 2. An Example of the Time Histories of the Recorded Data (ω_f = 3.16 rad/sec, and K_f = 1.41)



Forcing Function Periodic Time = $2\pi/\omega_f$ = 3.97 sec.
Controlled Element Periodic Time = $2\pi/\omega_n$=1.40 sec.

Figure 3. An Example of the Time Histories of the Recorded Data (ω_f = 1.58 rad/sec, and K_f = 2.00)

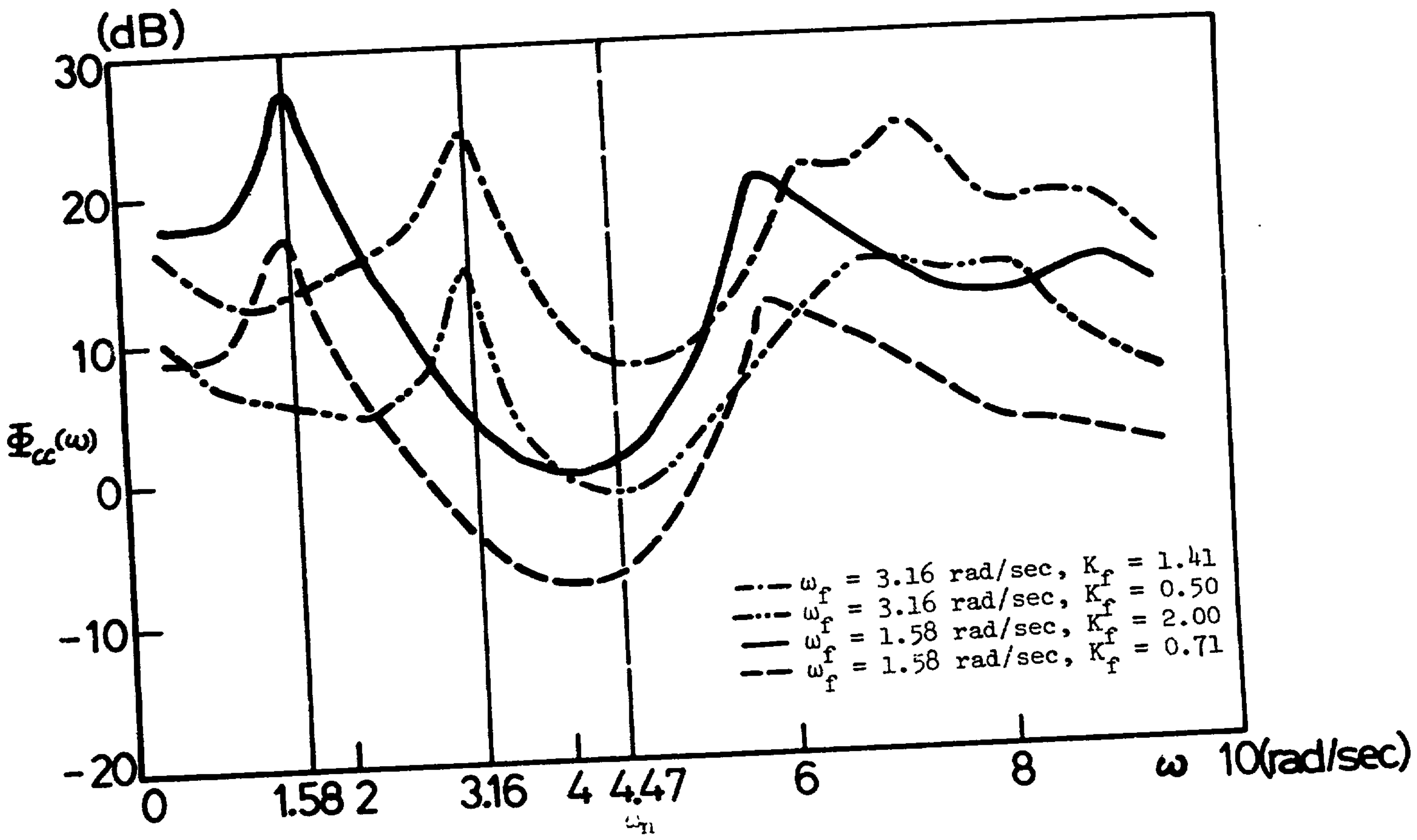


Figure 4. Examples of the Power Spectra of the Pilot Control Output

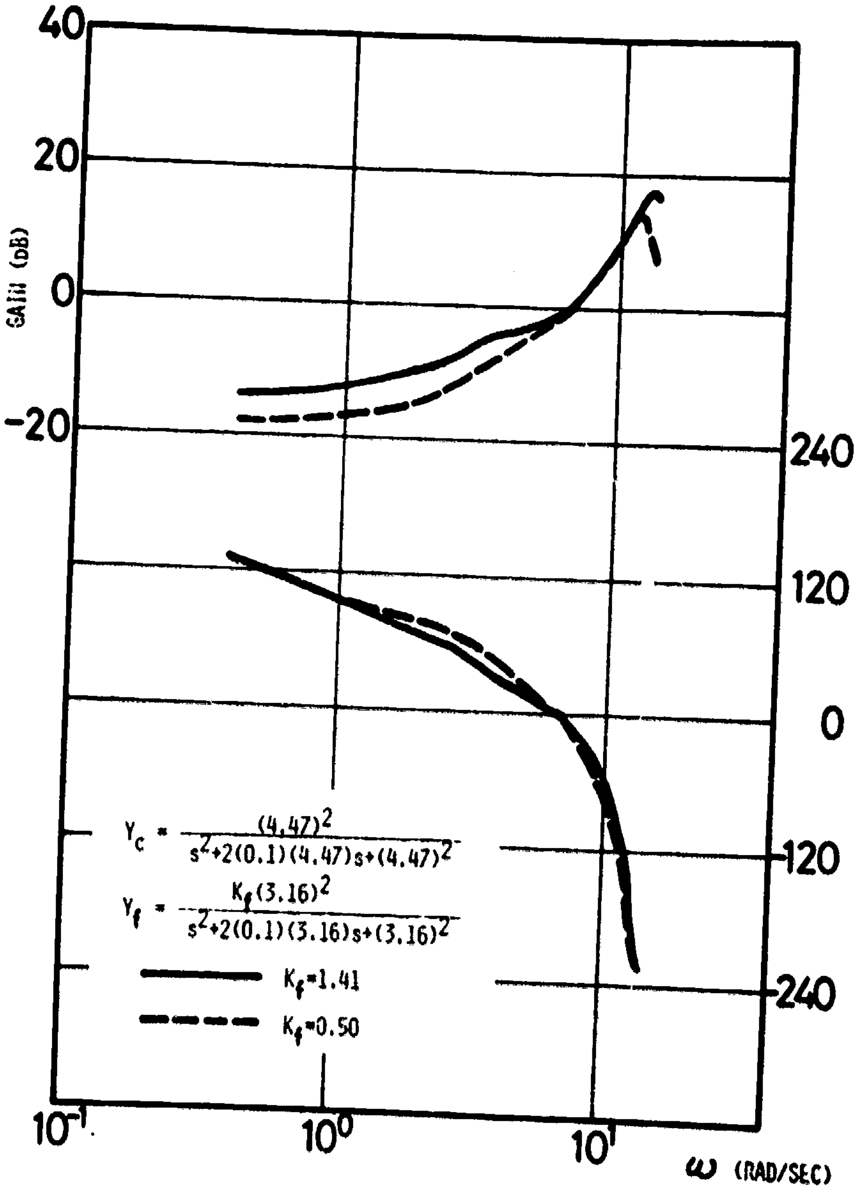


Figure 5. Comparison of Pilot Frequency Responses when ω_f=3.16 rad/sec.

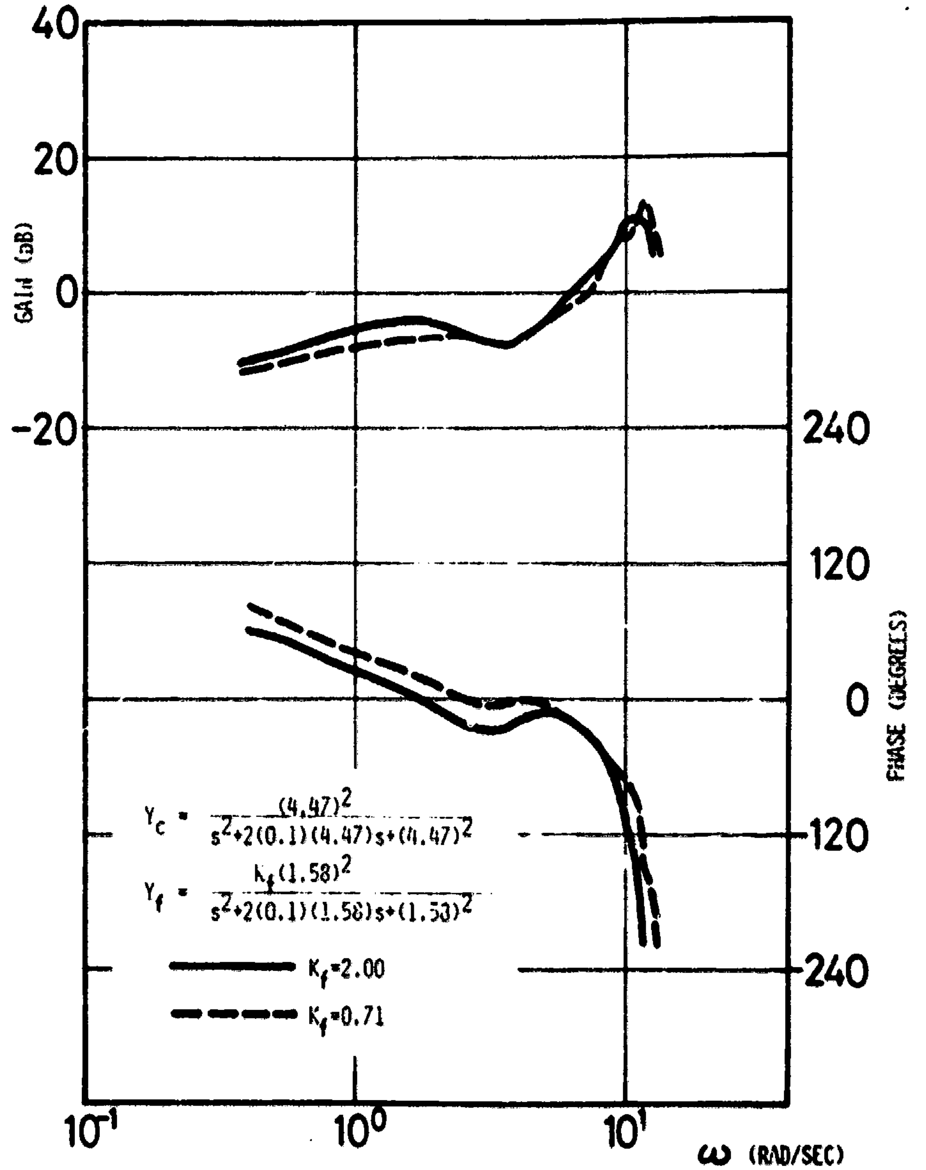


Figure 6. Comparison of Pilot Frequency Responses when ω_f=1.58 rad/sec.

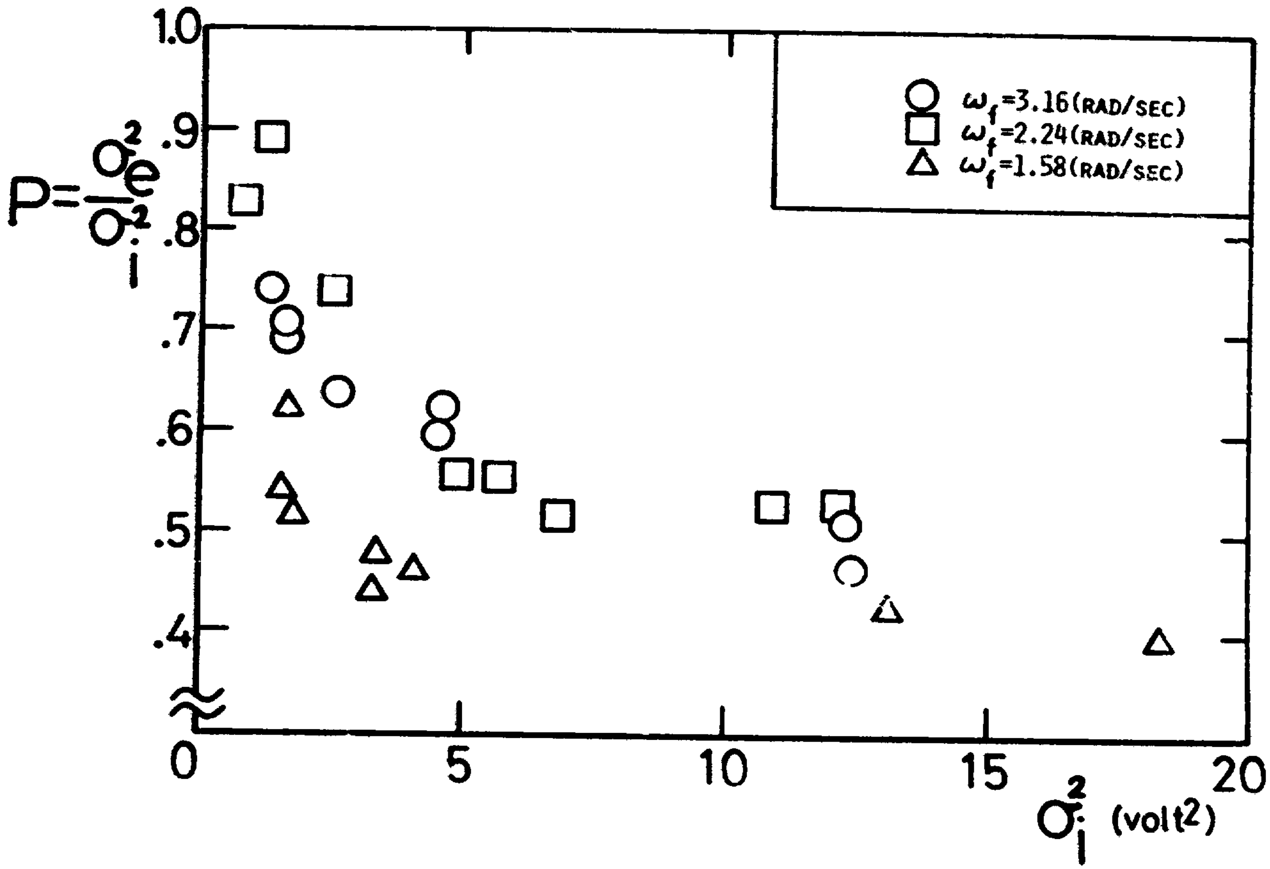


Figure 7. Effect of σ_i^2 and ω_f on Pilot Control Performance