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A HUMAN OPERATOR GUNNER MODEL FOR A TRACKING TASK WITH INTERRUPTED OBSERVATIONS IN AN ANTIAIRCRAFT ARTILLERY SYSTEM

CHEN-FU YU, PhD

SYSTEMS RESEARCH LABORATORIES, INC.
2800 INDIAN RIPPLE ROAD
DAYTON, OHIO 45440

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AEROSPACE MEDICAL DIVISION
AIR FORCE SYSTEMS COMMAND
WRIGHT-PATTERSON AIR FORCE BASE, OHIO 45433

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FOR THE COMMANDER

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This report describes the development of a mathematical model (blanking model) for a human operator's tracking performance under visual interruptions via blanking the target in a simulated manned antiaircraft artillery system. The basic ideas of the Luenberger observer theory are extended to develop an observer model with time-varying gains. The model consists of a reduced-order observer, a feedback controller, and two noise components. The blanking model is then obtained from the general model under an exponential-gain assumption. Four blanking time constants associated with

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20. ABSTRACT (Continued)

the exponential gains are introduced to relate to the human operator's short-term memory. The parameters of the model are identified from a curve-fitting computer program.

Model predictions of both azimuth and elevation tracking errors for several flyby and maneuvering trajectories are shown to be in excellent agreement with the empirical data obtained from the blanking experiments conducted at AFAMRL/HEF, Wright-Patterson AFB, Ohio. It is concluded that the blanking model developed in this report is a predictive model for a gunner's tracking performance with interrupted observations.

PREFACE

This report documents a study performed by Systems Research Laboratories, Inc. (SRL), Dayton, Ohio, for the Air Force Aerospace Medical Research Laboratory (AFAMRL), Human Engineering Division, Manned Threat Quantification Program. This work was performed under Contract F33615-79-C-0500. The Contract Monitor was Dr. Carroll N. Day, and the Technical Manager was Capt. George J. Valentino. The SRL Project Manager was Mr. Kaile Bishop.

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Section 1
INTRODUCTION

One of the fundamental goals of the Air Force in its Manned Threat Quantification (MTQ) Program is to evaluate and predict the effectiveness of a manned antiaircraft artillery (AAA) system. The main problem associated with it is to develop a mathematical model(s) for the gunner so that the analysis and computer simulations of the man-in-the-loop system become possible.

The mathematical modeling of a trained human operator (gunner) in a simulated AAA system has been studied by many investigators during the past 20 years. A brief comparison of different human operator models was listed in Kou and Glass (1977). The human operator was basically treated as a feedback controller or compensator in the closed loop system. McRuer and Krendel (1974), using a frequency domain analysis, represented the human operator with a linear transfer function and a remnant element. Kleinman and Perkins (1974), using a stochastic optimal control formulation, quantified the human operator as an optimal controller and estimator with respect to a lost functional and constraints. Phatak and Kessler (1977), simplifying the optimal control model, obtained a PID model. Finally, Kou et al. (1979), using a reduced order observer, characterized the human operator as a linear feedback controller and a Luenberger state reconstructor with all system noises lumped into one remnant. All of these models were able to explain their laboratory data under certain specified tracking conditions.

It has been observed (as expected) that a well trained human operator responds consistently in performing his assigned control tasks; that crucial fact is particularly true when the control tasks are relatively simple. In the manned AAA system considered here, the human operator plays the role of "stabilizing" the closed loop system. His control characteristics, of course, depend on what kind of information is available for him. In this regard, the human operator model consists of two parts: the first one deals with how the human operator processes the available information for his decisions; the second one deals with how his actual control outputs are generated from some decision variables. To describe these two parts mathematically, both the time domain and the frequency domain approaches can be applied. The optimal control model, the PID model, and the observer model were all based on the time domain descriptions. The time domain approach has the advantage of being able to describe a human operator's dynamic responses in a more direct and natural way. See McRuer (1980) for a discussion of the two approaches.

With the neglect of time delays in the system, it can be easily realized that the observer model and the optimal control models have very similar structures. In the observer model, a Luenberger observer provided state reconstructions, whereas, in the optimal control model, a Kalman filter provided the state estimations. The observer model became a very useful model for the following reasons:

1. It has simple structures.
2. The parameters of the model can be identified from a systematic curve-fitting program.
3. It requires shorter computer execution time.
4. It provides good model predictions.

NEED TO DEVELOP A BLANKING MODEL

In many situations, a human operator's tracking performance is subjected to external interruptions. The interruptions are, in the real world, due to electronic/optical countermeasures or weather conditions like fog, visibility, etc. As in the previous studies, the human operator perceives his tracking error as a displayed feedback signal. However, in this case, the error signal is no longer available during the interruptions via blanking the target. Using the optimal control model, Kleinman et al. (1979) has done an initial study of this condition in which the effects of blanking on tracking performance were modeled via increasing the observation noises. In this report, we applied the observer formulation to develop a more general model suitable for predicting tracking performance under random interruptions.

Section 2

THE MANNED AAA TRACKING SYSTEM

The general configuration of the manned AAA tracking system is shown in Figure 1. A detailed description of the AAA simulator can be found in Rolek (1977).

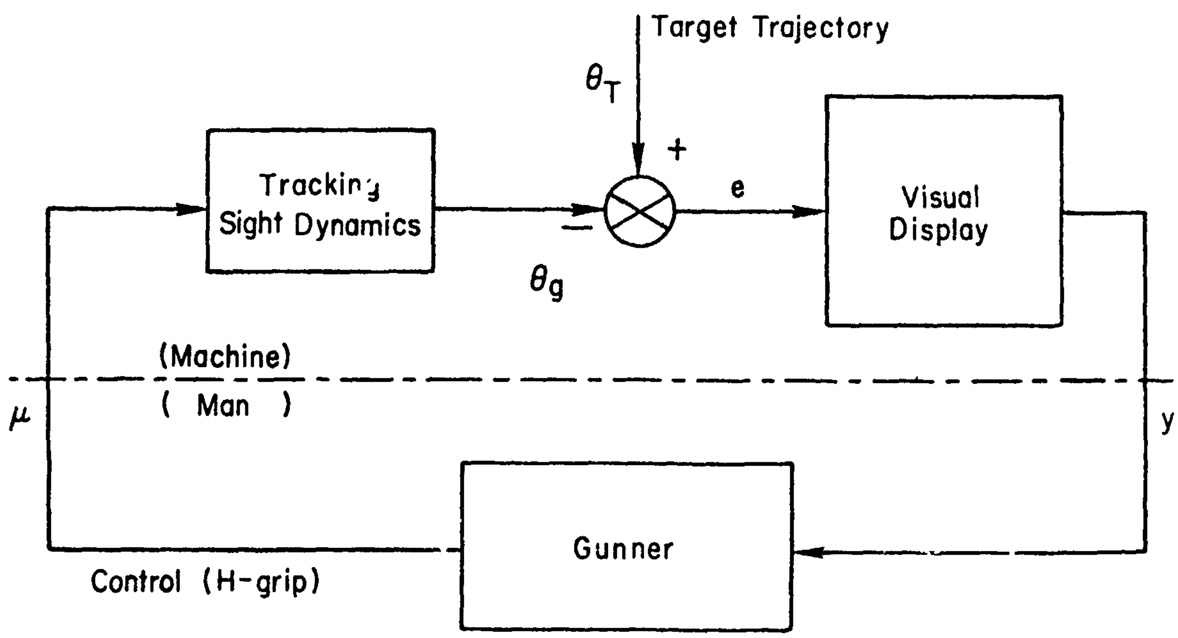


Figure 1. General Configuration of the Manned AAA System

The machine part of the system consists of the tracking sight dynamics (the plant), the target trajectory input, and the visual display (a two-dimensional screen). The tracking sight dynamics relates the tracking sight angle "θ_g" to the gunner's control output "μ" via a rate control. The visual display provides the information of the tracking error to the gunner. The tracking error "e" is the difference between the target angle "θ_T" and the tracking sight angle "θ_g." The tracking system line of sight coincides with the center of the visual display. Therefore, the horizontal and the vertical components of the error signal represent, respectively, the azimuth and the elevation components of the tracking error seen by the gunner. The task of the gunner is to constantly direct the tracking sight angle to the target angle. In this study, a single gunner tracks both the azimuth and the elevation target positions. The elevation tracking loop can be decoupled from the azimuth component, where the azimuth tracking loop cannot be separated from the elevation one. The reason for the latter is due to the fact that the displayed azimuth tracking error depends on the elevation tracking sight angle. However, one can treat the elevation tracking loop independently at first, and then treat the azimuth tracking loop with elevation tracking angle as an input variable. In this sense, the two loops are treated as decoupled, and Figure 1 can be used to represent either the azimuth or the elevation tracking loop.

THE MATHEMATICAL MODEL OF THE TRACKING SIGHT DYNAMICS AND THE VISUAL DISPLAY

The tracking dynamics can be approximately represented by a transfer function with a pole at the origin.

Specifically, we have:

$$\dot{\theta}_g(t) = 1.34\ \mu(t) \qquad \text{for elevation}$$

$$\dot{\theta}_g(t) = 1.28\ \mu(t) \qquad \text{for azimuth}$$

The displayed error "y" and the actual error "e" are related via the elevation tracking angle:

$$y(t) = c\ e(t)$$

where

$c = 1$ for elevation

$c = \cos(\theta_g)$ for azimuth

θ_g = elevation tracking angle

Note that, under optical interruptions via blanking the target, the displayed tracking error $y(t)$ cannot be seen from the screen, but the actual error $e(t)$ is still defined the same way.

Section 3

GENERAL TRACKING CHARACTERISTICS OF A GUNNER

In his attempt to minimize the tracking error in an entire run, the gunner has to adopt a feedback strategy. The gunner is actually involved with a multistage decision problem with unpredictable disturbances (target motion) driving the system. The gunner's main effort is to stabilize the closed loop system. More specifically, if the displayed tracking error becomes large, he actuates control input to reduce the error; if the target appears moving faster and faster, he responds to it by increasing the gunsight speed. Thus, the two important decision variables for the gunner are the displayed error signal and the estimated target velocity generated by him. Due to the crossfeed between the target motion and the gunsight motion, the gunner is usually "forced" to assume that the target will remain at a constant speed within the next moment. By continuously perceiving how the tracking errors change, the gunner can constantly reconstruct and update the target velocity. However, if the tracking task becomes too difficult for a gunner to follow, the gunner may simply change or give up the feedback strategy described above. The result is a so-called crossover regression. The gunner may simply set the tracking sight ahead of the target and prepare for future control action. Also, each gunner is expected to have his own way to "compensate" for his previous misjudgments or uncertainties in performing his tasks. (This latter part of response characteristics cannot be modeled mathematically without further understanding of how human operators' uncertainties propagate within the task-dependent system.)

Tracking under interruptions can also be understood or described via the above decision variables and the feedback principles. Under interruptions via blanking the target, the updating process is no longer possible due to lack of feedback signals. The gunner continues to control the system based on his internal perception of the environment.

Section 4

THE ELANKING EXPERIMENTS AND THE TRACKING DATA

Three trained subjects were asked to track a moving target (simulated aircraft) on the display screen during an entire run of approximately 40 seconds. The subject used a rate control to direct the target sight to follow the target. The visual screen was blanked periodically according to one of the following five blanking conditions (last portion of a cycle is blanked):

	Blanking Duration	Percentage of Time Blanked
(C1)	1.5 seconds	25 percent
(C2)	3 seconds	25 percent
(C3)	6 seconds	25 percent
(C4)	3 seconds	50 percent
(C5)	No blanking during the entire run (baseline)	

There were four preprogrammed, deterministic, input target trajectories, namely the 2×2 flyby, the 4×5 flyby, the recon, and the weapon delivery. At each run, the subject had no information about (a) which of the four trajectories was used as the driving input, and (b) which of the five blanking conditions was being applied. With that experimental design, the subject was considered as tracking unknown target motion under pseudo-random interruptions. Each of the 20 tracking conditions was run 40 times and the time history of the tracking errors recorded. The means and the standard deviations were then computed from the 40 replications. Thus, the whole experiment generated 20 sets of ensembled tracking data per subject. One subject's tracking data were selected for the modeling and simulation study.

SOME OBSERVATIONS ON THE TRACKING DATA

The three subjects had reasonably consistent tracking responses. The "patterns" of the mean tracking errors and the standard deviations were very similar. In some situations, the magnitudes of the tracking data differed slightly. The difference could be explained as due to a subject's tracking skill or his individual psychophysical parameters.

The degradation of tracking performance due to blanking was very significant. The "induced errors" (relative to no blanking data) depended on blanking duration, percentage of time blanked, and local characteristics of the target motion. For example, if the target acceleration reversed its direction within a long blanking, the peak tracking errors were significantly much larger than that of the no blanking case.

Section 5

OBSERVER THEORY AND STATE ESTIMATIONS

Luenberger observer theory has been applied successfully to the design of deterministic feedback control systems in many areas during the past decade (Luenberger, 1966 and 1971). The basic concept of asymptotic stability associated with the observer theory can be generalized to a version of stochastic stability for a stochastic estimator (Tse and Athens, 1970; Tarn and Pasis, 1976). This section summarizes some basic ideas of the observer theory and introduces necessary mathematical modeling techniques to be used in developing a gunner model for tracking tasks with interrupted observations.

Before proceeding, we introduce the following purely matrix-theoretic lemma, which was considered as the cornerstone of the Luenberger observer theory.

Assume that the two matrices A and C form an observable pair (A, C). Let K be a matrix of appropriate dimension. Then, all the eigen values of the matrix (A-KC) can be selected to have preassigned values by selecting a suitable K. In particular, the matrix (A-KC) becomes a stable matrix for a suitable K.

Let $X(t)$, $\mu(t)$, and $Y(t)$ denote, respectively, <u>the state</u>, <u>the control</u>, and <u>the observation</u> at time <u>t</u> of a linear controlled system (*):

$$\begin{aligned} \dot{X}(t) &= A\,X(t) + B\,\mu(t) \\ Y(t) &= C\,X(t) \end{aligned} \qquad (*)$$

In the manned AAA tracking system, the state $X(t)$ has two components; the first one represents the tracking error and the second one denotes the target velocity. The human operator's control output $\mu(t)$ depends on the above two decision variables. However, only the tracking error $Y(t)$ is directly available to the human operator. The target velocity has to be reconstructed as an unknown initial condition. The simple deterministic setting (*) is used here for illustrating the basic modeling approach based on the observer theory. In the actual applications, the control $\mu(t)$ and the observation $Y(t)$ are allowed to contain the human operator's motor noises and his observation noises, respectively.

The generalization from the simple setting (*) to a stochastic one was carried out in a straightforward manner without rigorous mathematical justifications.

If the system (*) is <u>observable</u>, then the observation $Y(s)$, $0 \leq s \leq t$, contains "enough" information to reconstruct the whole state $X(t)$. The previous lemma provides a necessary and sufficient condition for the system to be observable. Let $\hat{X}(t)$ denote a <u>reconstructed state</u> at time <u>t</u>, and consider the following dynamics (called an <u>observer</u>):

$$\dot{\hat{X}}(t) = A\,\hat{X}(t) + B\,\mu(t) + K\left[Y(t)-C\hat{X}(t)\right] \tag{**}$$

The initial condition $\hat{X}(o)$ can be assigned arbitrarily, and the observer gain K is to be designed or identified.

Define the estimation error $\Sigma(t)$ as

$$\Sigma(t) \equiv \hat{X}(t) - X(t)$$

From (*) and (**), it can be shown easily that

$$\dot{\Sigma}(t) = (A-KC)\,\Sigma(t) \tag{5-1}$$

$$\Sigma(o) = \text{initial estimation error} \tag{5-2}$$

Thus, by selecting a suitable K, the estimated state $\hat{X}(t)$ generated from (**) approximates the true state $X(t)$ asymptotically for any initial error $\Sigma(o)$. <u>The initial time does not need to be zero; it can be any specified time instant</u>.

The observer (**) reconstructs all the components of the state $X(t)$. We like to have a <u>reduced-order observer</u> which reconstructs only those state components which are not directly observable. To proceed, let $X(t) = [Y(t), w(t)]^T$, where $Y(t)$ is observable, and $w(t)$ needs to be reconstructed. Write (*) as

$$\begin{cases} \dot{Y} = A_{11}\, Y + A_{12}\, w + b_1\, \mu \\ \\ \dot{w} = A_{21}\, Y + A_{22}\, w + b_2\, \mu \end{cases} \tag{5-3}$$

$$Y = [I \vdots 0] \qquad \begin{bmatrix} Y \\ \cdots \\ w \end{bmatrix}$$

It can be shown that if (A, C) is an observable pair, then (A_{22}, A_{12}) is also an observable pair. Consider both $Y(t)$ and $\mu(t)$ as given; then the following dynamics (called a <u>reduced-order observer</u>) provide a way to update the state component $\hat{w}(t)$:

$$\dot{\hat{w}} = A_{22}\, \hat{w} + A_{21}\, Y + b_2\, \mu + k \left[\dot{Y} - A_{11}\, Y - A_{12}\, \hat{w} - b_1\, \mu\right] \tag{5-4}$$

Define the estimation error as $\Sigma(t) = \hat{w}(t) - w(t)$, then we have

$$\dot{\Sigma}(t) = \left(A_{22} \;\; -k\, A_{12}\right) \Sigma(t) \tag{5-5}$$

<u>Thus, for suitable</u> k, <u>the reduced-order observer</u> (5-5) <u>does indeed provide an asymptotic reconstruction of the unobservable part</u> $w(t)$.

In the manned AAA tracking system, (5-3) takes the following form:

$$
\frac{d}{dt}\begin{pmatrix} y \\ \dot{\theta}_T \end{pmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}\begin{pmatrix} y \\ \dot{\theta}_T \end{pmatrix} + \begin{bmatrix} b \\ 0 \end{bmatrix} \mu + \begin{pmatrix} 0 \\ 1 \end{pmatrix} \ddot{\theta}_T
$$

$$
Y = [I \ \vdots \ 0] \begin{bmatrix} y \\ \dot{\theta}_T \end{bmatrix} \tag{5-6}
$$

The human operator's internal model of the tracking system is not necessarily exactly the same as above. Let the target model of the human operator be written as:

$$
\frac{d}{dt}\dot{\theta}_T = -g(t)\,\dot{\theta}_T \tag{5-7}
$$

Then a mathematical description of the human operator's internal model of the closed loop system can be expressed as follows:

$$
\frac{d}{dt}\begin{pmatrix} y \\ \dot{\theta}_T \end{pmatrix} = \begin{pmatrix} 0 & 1 \\ 0 & -g(t) \end{pmatrix}\begin{pmatrix} y \\ \dot{\theta}_T \end{pmatrix} + \begin{pmatrix} b \\ 0 \end{pmatrix} \mu \tag{5-8}
$$

$$
Y = [I \ \vdots \ 0] \begin{bmatrix} y \\ \dot{\theta}_T \end{bmatrix}
$$

Defining the estimation error of the target velocity as the difference between the true target velocity $\dot{\theta}_T$ [from (5-6)] and the estimated velocity [from (5-8)], we have:

$$\beta(t) \equiv \dot{\theta}_T - \hat{\dot{\theta}}_T(t)$$

$$\dot{\beta}(t) = -[k+g(t)]\ \beta(t) + \ddot{\theta}_T + g(t)\ \dot{\theta}_T \qquad (5-9)$$

To associate some intuitive meanings to the observer gain "k" in (5-9), consider the following special situations: let the true target motion be that of a constant velocity (i.e., $\ddot{\theta}_T = 0$), and let the human operator's internal model of target motion be also that of a constant velocity [i.e., $g(t) = 0$]. Then (5-9) has the following simple solution:

$$\beta(t) = \beta(0)\ e^{-kt} \qquad (5-10)$$

The observer gain k appears as the inverse of a time constant of the exponential function in (5-10). Thus, the gain is a measure of how fast the human operator reduces his initial estimation error $\beta(0)$ to zero. With a fixed gain k, the larger the previous error is, the more improvement is made in correcting the error (see Figure 2).

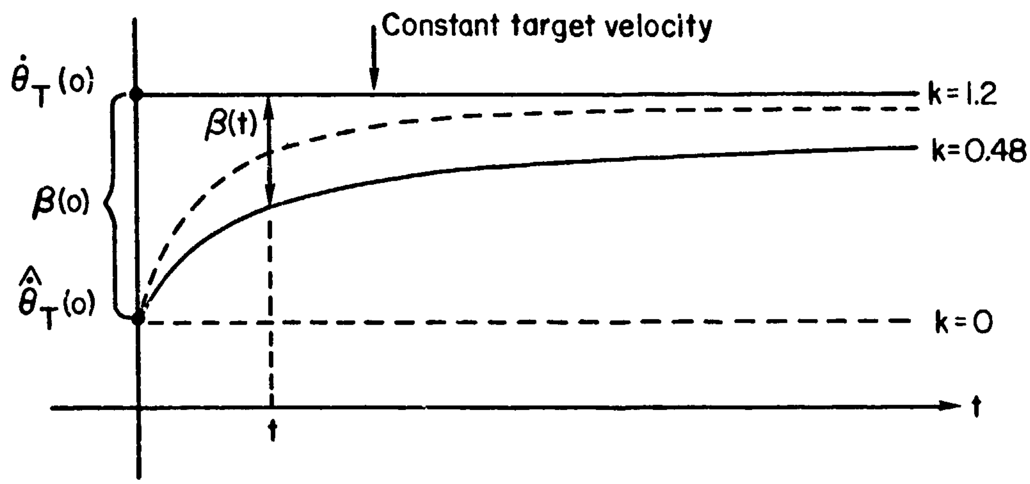


Figure 2. Exponential Reconstruction of Target Velocity

Note that if the human operator assumes that the target has acceleration with local bandwidth $g(t)$, then the "effective gain" becomes $[k+g(t)]$. This is also a theoretical justification for considering time-varying gains in developing a general observer model. The interpretation also provides a way of incorporating a human operator's adaptive internal model of target motion into an observer model in a natural way.

It is interesting to compare formally the Luenberger observer with a Kalman filter. With motor noises and observation noises taken into consideration, we have the following stochastic system:

$$\dot{X} = AX + B\mu + \text{driving noises}$$

$$Y = CX + \text{observation noises}$$

The associated Kalman filter provides an optimal state estimation for $X(t)$ (a random process) based on noise corrupted observations $Y(s)$, $0 \leq s \leq t$. For example, see Nahi (no date) or Kushner (1971). The Kalman filter has exactly the same form of dynamics as in (**). However, in this case, the Kalman gain $K(t)$ is no longer free. It is an "optimal gain" determined from the associated Ricotti equations which, in turn, can be computed independently of the observation data. The term $[Y(t)-C\hat{X}(t)]$ is a (random) innovation process; it provides a new and unpredictable part of the information. The filtering gain $K(t)$ can be viewed as the optimal weighting factor for the innovation $[Y(t)-C\hat{X}(t)]$ at time t. Without the assumption of optimality, as the case in the observer approach, the gain $K(t)$ can be viewed as representing the human operator's estimation "strategy" conditioned on his limitations and his tracking environments. The asymptotic state estimation is, thus, merely a result of processing the information "constructively" rather than optimally.

Section 6

OBSERVER MODEL WITH TIME VARYING GAINS

This section develops a general observer model for the manned AAA tracking system. The gunner's tracking performance is quantified as a feedback controller. The feedback available to him consists of the displayed signal (observation) and the nonvisual feedback generated through his control interaction with the dynamics of the system (perception). With this understanding, we assume that the gunner has an internal model of the closed loop system driven by his observation and his perception. It is natural to further assume that the gunner's control output is completely based on that internal model. Also, with the rate control in mind, it is not difficult to realize that the gunner's whole tracking efforts are basically designed to generate a key internal state variable--the target velocity. The gunner's internal model of target velocity was considered as the key variable in his feedback strategy. To quantify the gunner's internal target velocity, we assume that the internal velocity is actually generated via a Luenberger observer or state reconstructor. The associated observation or reconstruction gains are, in general, time varying. The gains depend on tracking conditions (information feedback), task difficulties (local trajectory characteristics), tracking skill, and the gunner's psychophysical parameters. Finally, we assume that the gunner's feedback control law is linear in his observation and his perception. The closed loop model structure is shown in Figure 3. Items 1 to 6 summarize the modeling assumptions.

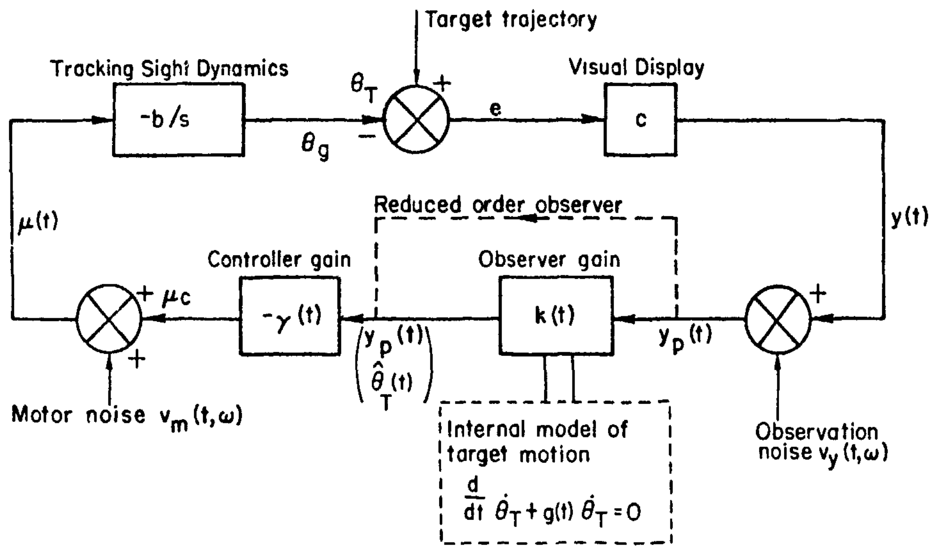


Figure 3. Observer Model with Time-Varying Gains

The modeling assumptions:

1.	Human operator's internal model of target motion (adaptive)	$g(t)$
2.	Gun dynamics and visual observation factor (learned by H.O.)	$-b/s$, c
3.	Feedback control law (linear)	$-\gamma(t)$
4.	Estimation error dynamics (reduced-order observer)	$k(t)$
5.	Time delay (neglected)	0
6.	Noise structures (white, with suitable covariances)	$Vm(t,\omega)$, $Vy(t,\omega)$

Define the state variables of the closed loop system as

$$X(t) = \left[x_1(t),\ x_2(t),\ x_3(t)\right]^T$$

where

$$x_1(t) = y(t) = c\ e(t) = c\left(\theta_T - \theta_g\right) \qquad \text{displayed tracking error}$$

$$x_2(t) = \dot{\theta}_T(t) \qquad \text{true target velocity}$$

$$x_3(t) = \beta(t) = \dot{\theta}_T(t) - \hat{\dot{\theta}}_T(t) \qquad \text{velocity estimation error}$$

In lieu of the assumptions 1 to 6, we have

$$\dot{\theta}_g(t) = -b\ \mu(t)$$

$$\mu_c(t) = -\gamma_1(t)\ y_p(t) - \gamma_2(t)\ \hat{\dot{\theta}}(t)$$

$$\dot{\beta}(t) = -\left[k(t)c + g(t)\right]\beta(t) + \ddot{\theta}_T(t) + g(t)\ \dot{\theta}_T(t) - kbcv_m(t,\omega)$$

$$y_p(t) = y(t) + v_y(t,\omega)$$

$$\mu(t) = \mu_c(t) + v_m(t,\omega)$$

The above equations can be written in matrix form as

$$\dot{X}(t) = A(t)\ X(t) + F\ \ddot{\theta}_T(t) + \text{noise terms} \tag{6-1}$$

where

$$A(t) = \begin{bmatrix} \frac{\dot{c}}{c} - bc\gamma_1 & c(1-b\gamma_2) & bc\gamma_2 \\ 0 & 0 & 0 \\ 0 & g(t) & -[k(t)c + g(t)] \end{bmatrix} \quad F = \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}$$

$$\text{Noise terms} = \begin{bmatrix} bcv_m(t,\omega) - bc\gamma_1 v_y(t,\omega) \\ 0 \\ -kbcv_m(t,\omega) \end{bmatrix}$$

Section 7

THE BLANKING MODEL AND PARAMETER IDENTIFICATIONS

The human operator's tracking performance is generally degraded under visual interruptions via blanking the target. This effect can be modeled directly via degrading the human operator's estimation gain k(t) and the control gain $\gamma(t)$. The induced uncertainties in performance can also be represented in the operator's motor noises. Figure 4 shows a typical situation of the effects of blanking on the gunner's capability to reconstruct the target velocity.

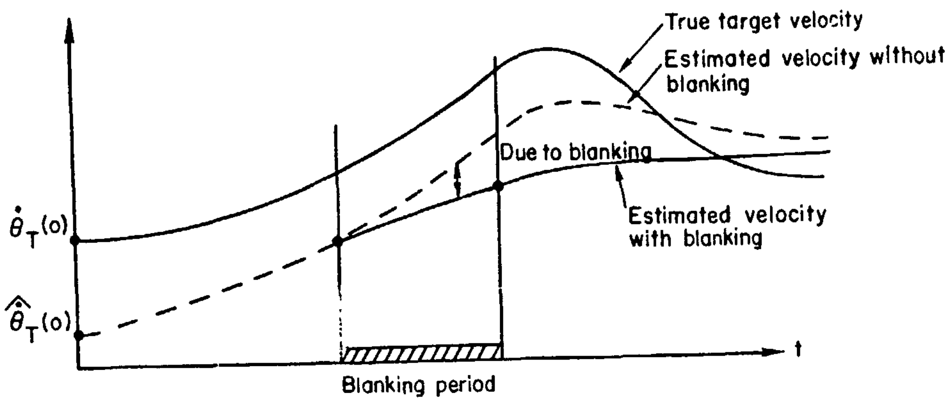


Figure 4. The Effects of Blanking--Degrading the Observer Gain

The blanking model used in the simulation studies was based on the following additional modeling assumptions:

1. The gunner's internal model of target motion is of the form $\ddot{\theta}_T = 0$ (no target acceleration is perceived by the gunner).

2. The gunner's observation noise can be lumped into the motor noise. The covariance of the motor noise is assumed to be of the form:

$$E\left[Vm(t,\omega)\ Vm(t',\omega)\right] \equiv \left[\alpha_1 + \alpha_2\left(\hat{\dot{\theta}}_T\right)^2 + \alpha_3\left(\hat{\ddot{\theta}}_T\right)^2\right]\delta(t-t')$$

The noise parameters α_1, α_2, and α_3 are allowed to have different values for different blanking durations.

3. <u>The observer gain k(t) and the controller gain $\gamma(t)$ are assumed to decrease exponentially as the blanking proceeds, and to increase exponentially as the blanking stops</u> (see Figure 5).

The time constants associated to the exponential functions are to be identified from experimental data. Both theoretic arguments and actual identification lead to the relation $b \cdot \gamma_2 \approx 1$, we assume that γ_2 is a constant.

PARAMETER IDENTIFICATIONS

The azimuth and the elevation curve-fitting identification programs developed in Kou et al. (1978) were modified slightly (data format, time step, etc.) to identify the base line parameters. The 2 × 2 flyby--no blanking-tracking data were used to obtain the following parameters:

Elevation Tracking

$$k = 0.48,\ \gamma_1 = -2.9,\ \gamma_2 = -0.77$$

$$\alpha_1 = 0.0003,\ \alpha_2 = 0.009,\ \alpha_3 = 1.3$$

Azimuth Tracking

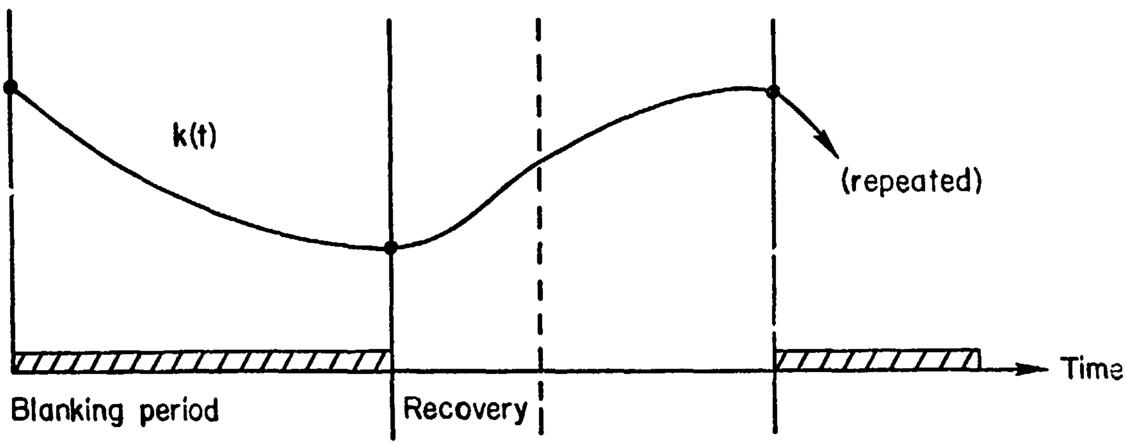
$$k = 1.2,\ \gamma_1 = -3.0,\ \gamma_2 = -0.78$$

$$\alpha_1 = 0.002,\ \alpha_2 = 0.003,\ \alpha_3 = 0.53$$

The time constants were identified from the 2 × 2 flyby--blanking condition 2--data:

$$\tau\ (\gamma_1,\ \text{blanking}) = 2.32 \text{ seconds},\ \tau\ (\gamma_1,\ \text{recovery}) = 1.92 \text{ seconds}$$

$$\tau\ (k,\ \text{blanking}) = 13.0 \text{ seconds},\ \tau\ (k,\ \text{recovery}) = 4.0 \text{ seconds}$$



$$\text{e.g.}\quad k(t) = k(o) \exp \frac{-t}{\tau\ (k,\ \text{blanking})}$$

Figure 5. Time Constants Related to Short-Term Memory

Section 8
COMPUTER SIMULATION RESULTS

The blanking model together with the identified parameters are ready to be implemented on a CDC Cyber 175 computer for simulation studies. The model predictions of the mean tracking errors and the standard deviations are computed in the following way.

With a fixed time step Δ sufficiently small ($\Delta = 0.03$ seconds in this study), the (slow) time-varying system (6-1) can be discretized as follows:

$$X_{n+1} = \phi_n X_n + \Gamma_n F \hat{\theta}_T(t_n) + \Gamma_n D \nu(t_n) \tag{8-1}$$

Where

$$t_n = n \cdot \Delta$$

$$X_n = X(t_n)$$

$$\nu(t_n) = Vm\,(t_n, \omega)$$

$$X_{n+1} = X\,(t_n+\Delta)$$

$$\phi_n = \exp\left[A(t_n)\Delta\right]$$

and

$$\Gamma_n = \int_{t_n}^{t_n+\Delta} \exp\left[A(t_n) \cdot s\right] ds$$

Taking expectation of both sides of (8-1), we have

$$\overline{X}_{n+1} = \phi_n \overline{X}_n + \Gamma_n F \hat{\theta}_T\,(t_n) \tag{8-2}$$

The covariance matrix P_n is defined as

$$P_n \equiv E\left[\left(X_n - \bar{X}_n\right)\left(X_n - \bar{X}_n\right)^T\right]$$

From (8-1) and (8-2), it can be shown that the matrix P_n satisfies the following equation:

$$P_{n+1} = \phi_n P_n \phi_n^T + \left(\Gamma_n D\right) \frac{Q\left(t_n\right)}{\Delta} \left(\Gamma_n D\right)^T \tag{8-3}$$

where

$$Q\left(t_n\right) = \alpha_1 + \alpha_2 \left[\dot{\hat{\theta}}_T \left(t_n\right)\right]^2 + \alpha_3 \left[\ddot{\hat{\theta}}_T \left(t_n\right)\right]^2$$

Thus, by solving the equations (8-2) and (8-3), we obtain the mean tracking error from the first component of $\bar{X}_n$ and the standard deviation from the square root of the first component $\left[P_n (1, 1)\right]$ of P_n. Figures 6 to 20 illustrate the typical simulation results for different trajectories and different blanking conditions.

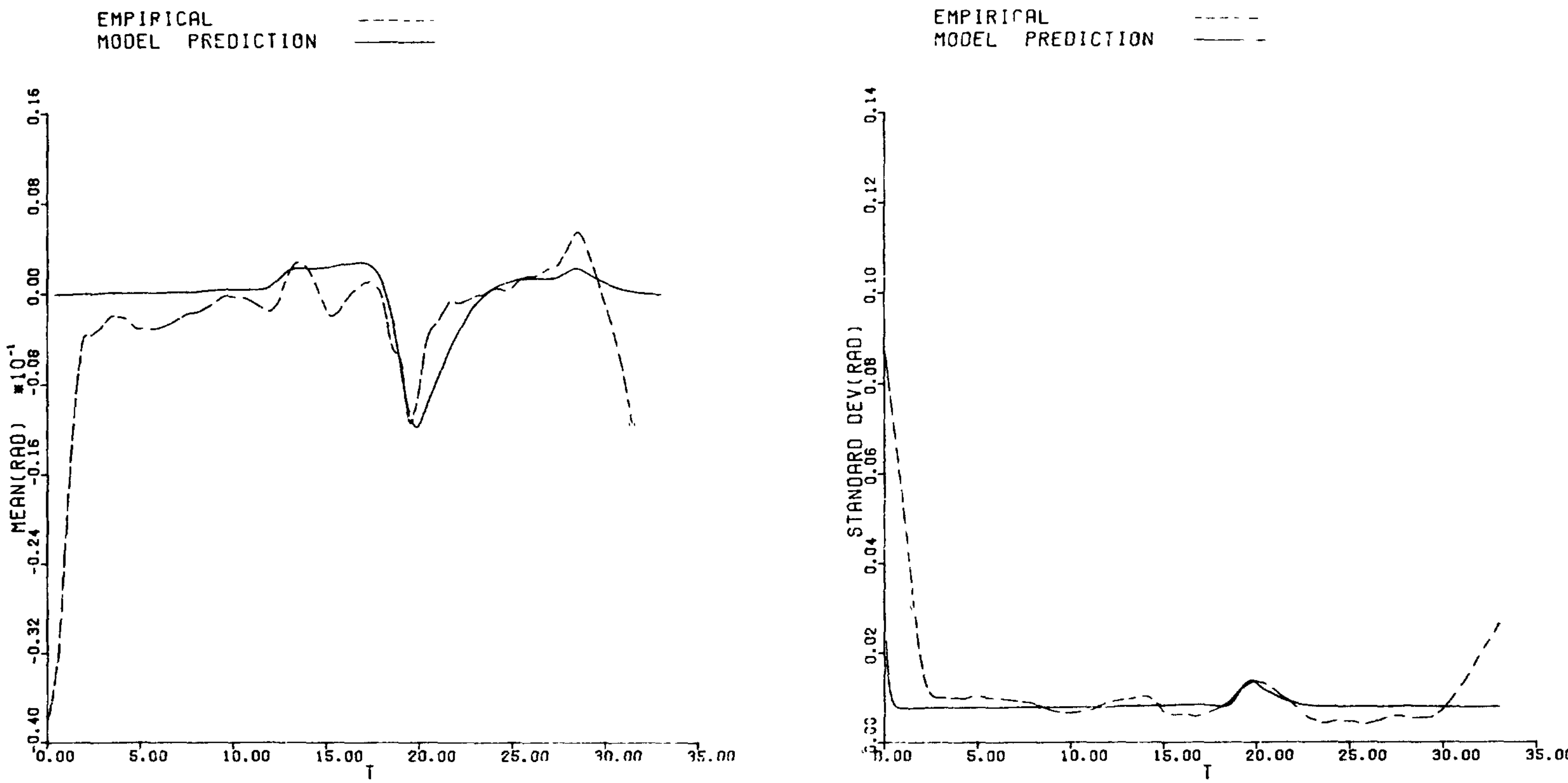


Figure 6. Elevation Simulation Result--Weapon Delivery-No Blanking

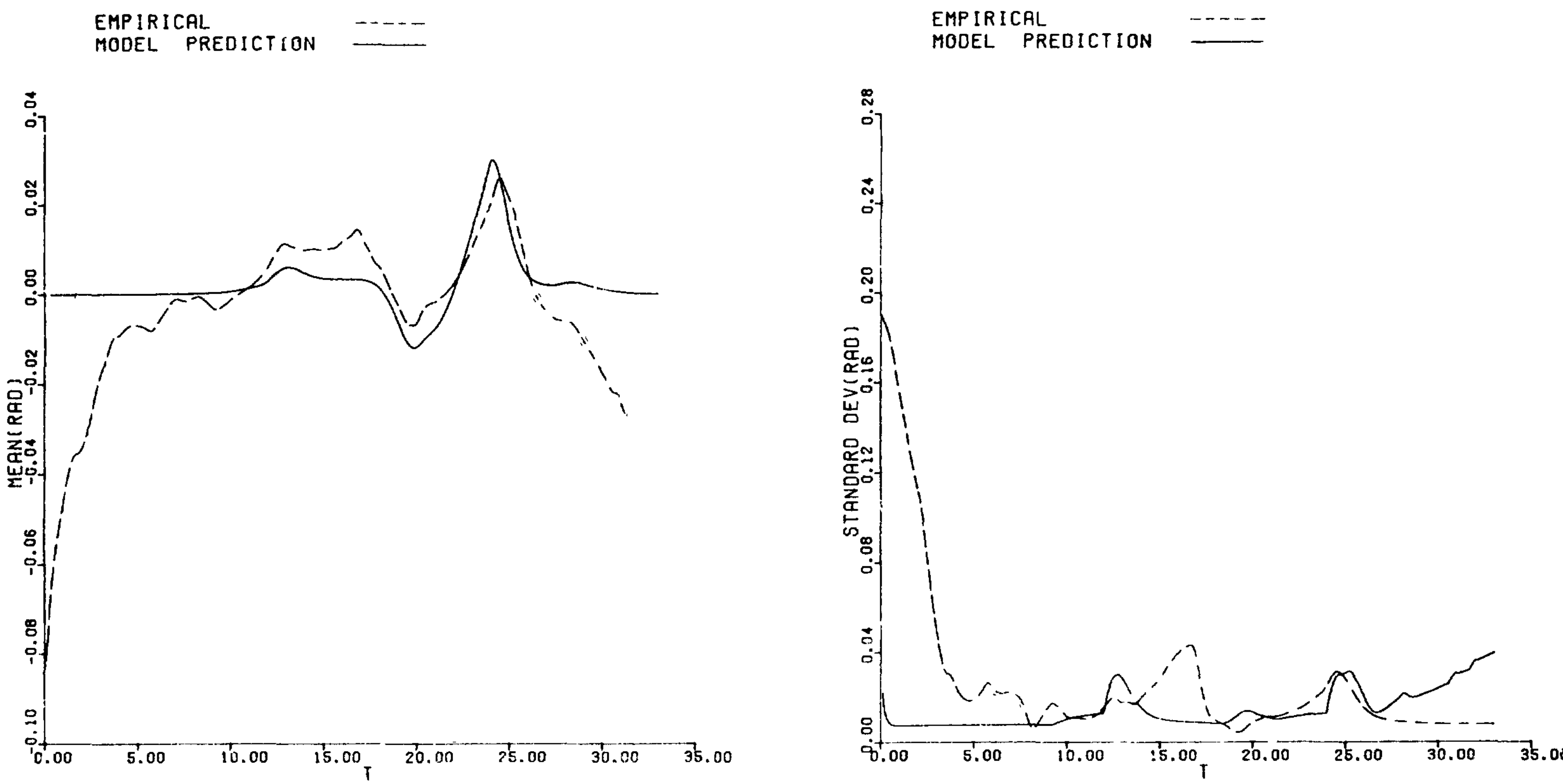


Figure 7. Elevation Simulation Result-Weapon Delivery--3 seconds, 25 percent

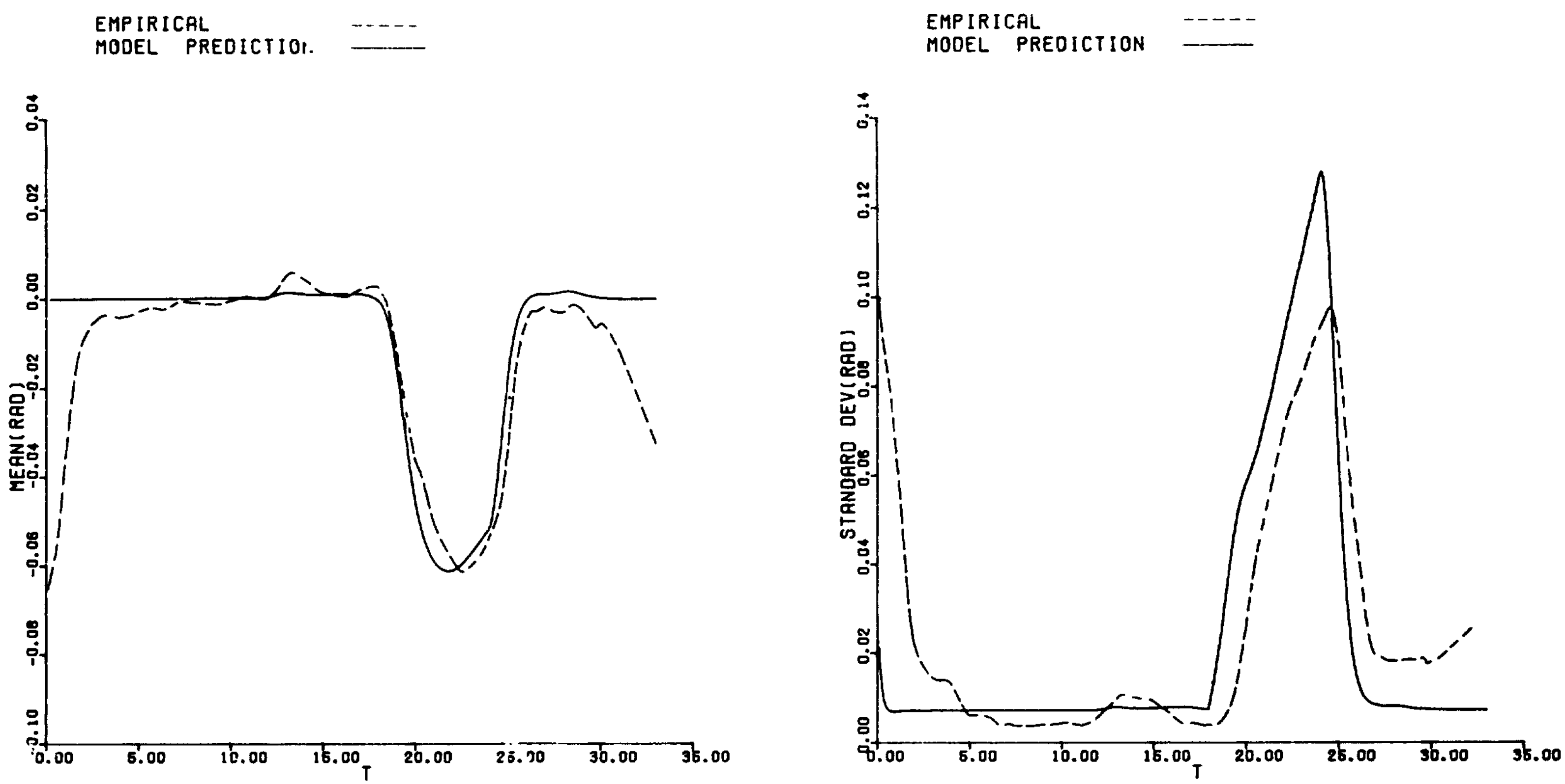


Figure 8. Elevation Simulation Result--Weapon Delivery--6 seconds, 25 percent

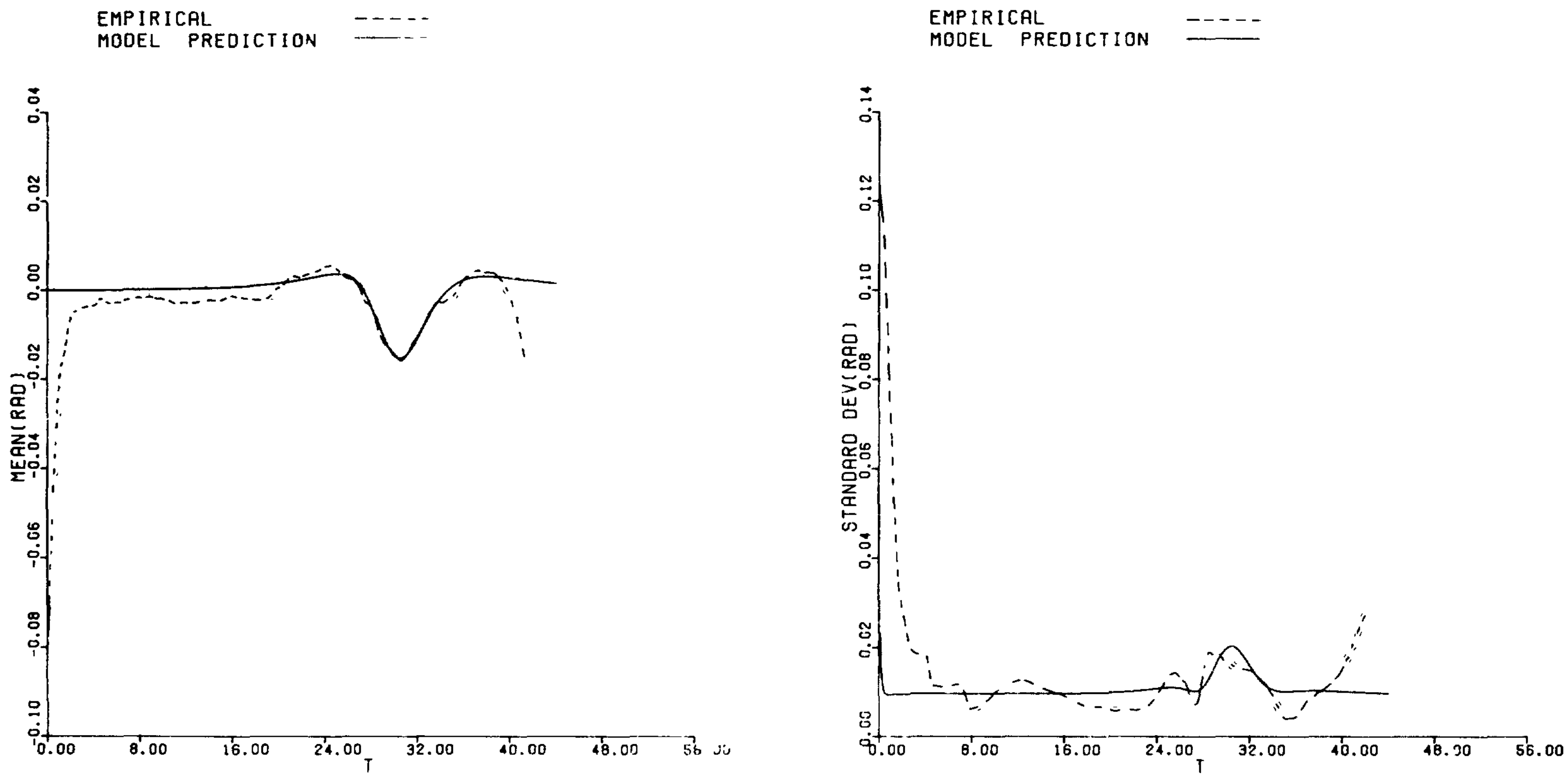


Figure 9. Elevation Simulation Result--2 x 2 Flyby--No Blanking

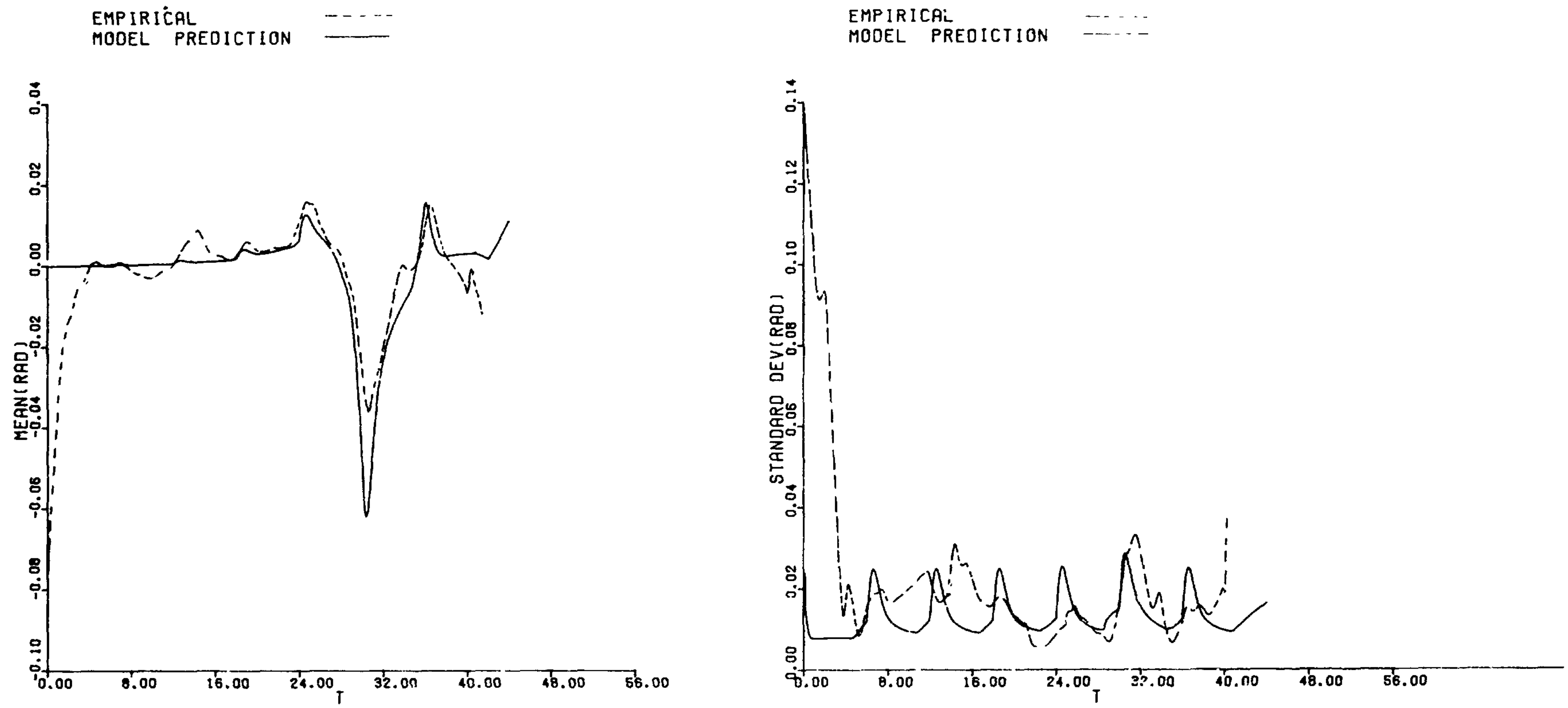


Figure 10. Elevation Simulation Result--2 x 2 Flyby--1.5 seconds, 25 percent

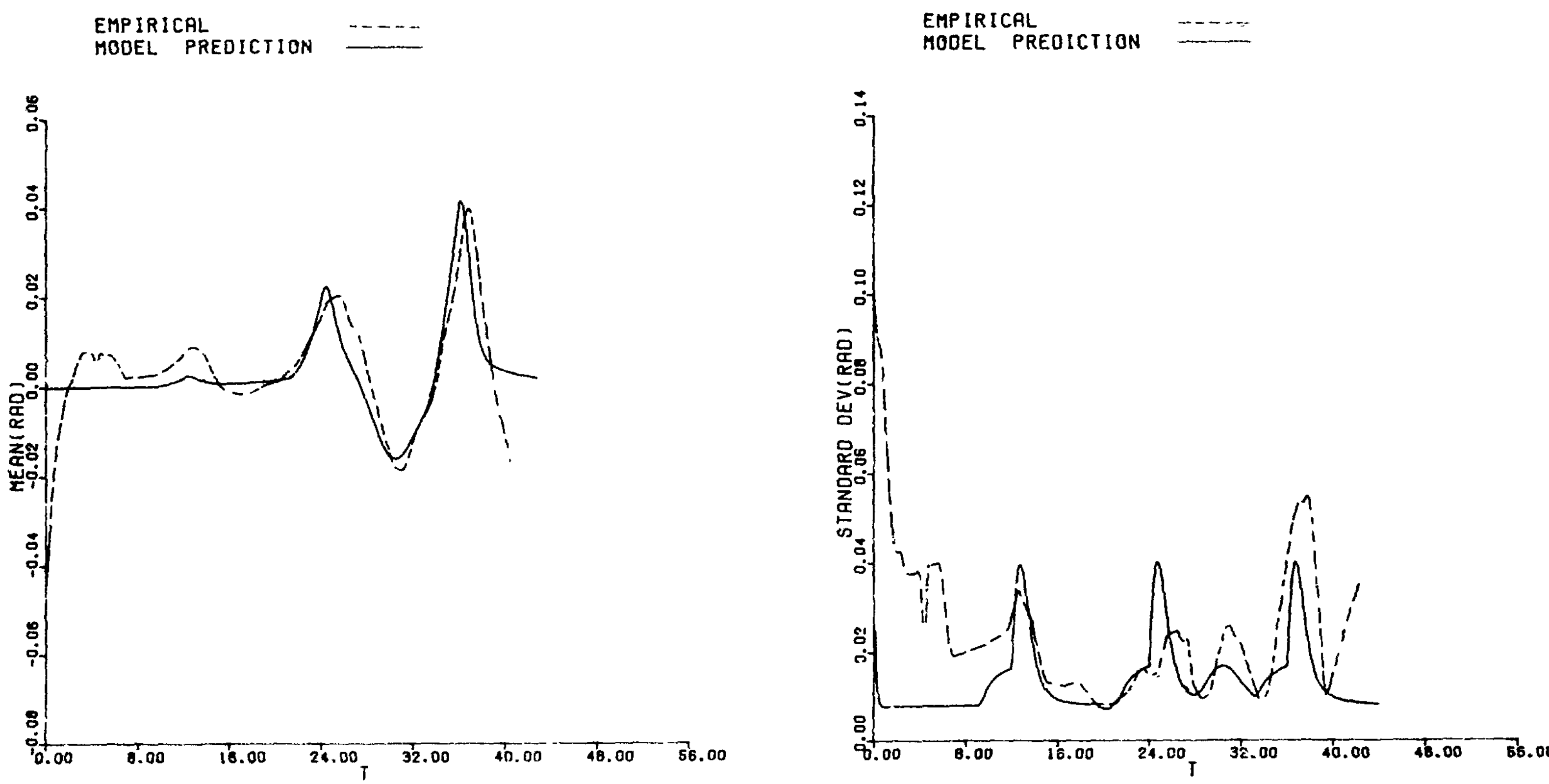


Figure 11. Elevation Simulation Result--2 x 2 Flyby--3 seconds, 25 percent

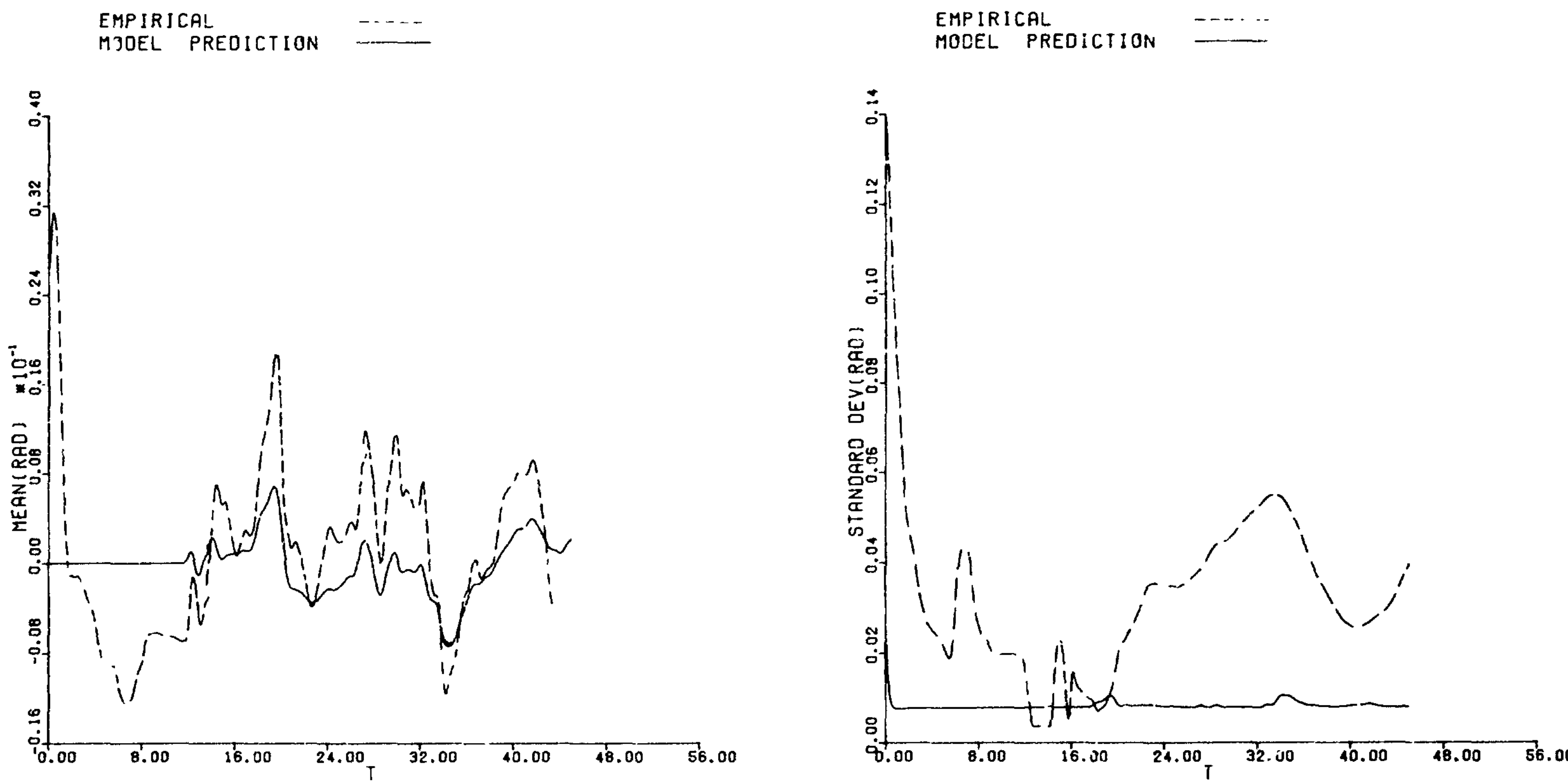


Figure 12. Elevation Simulation Result--Recon--No Blanking

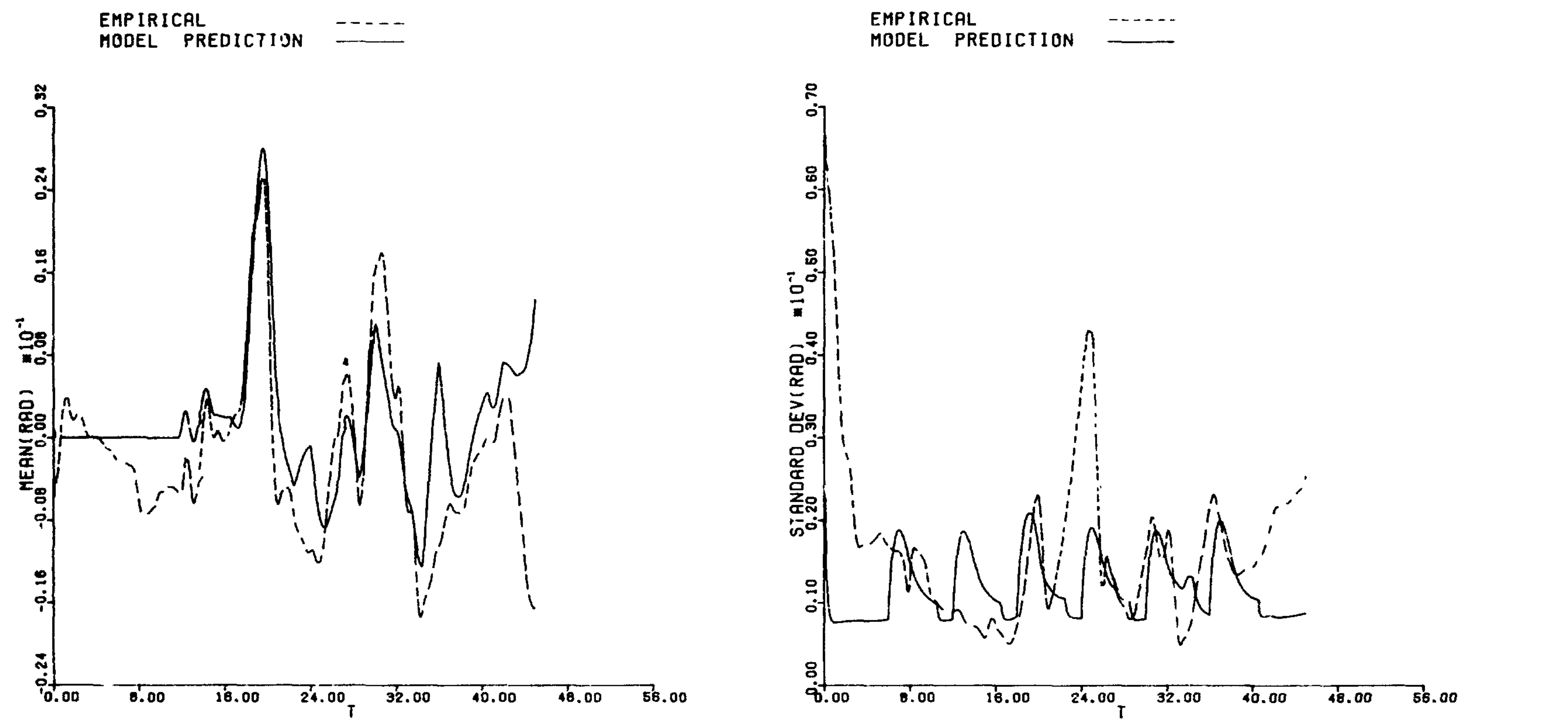
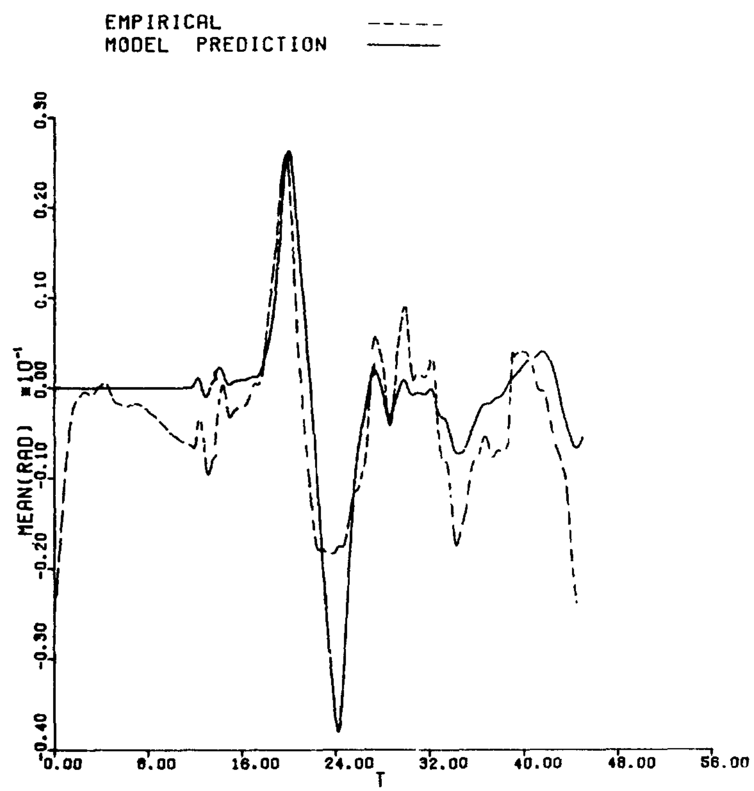


Figure 13. Elevation Simulation Result--Recon--1.5 seconds, 25 percent



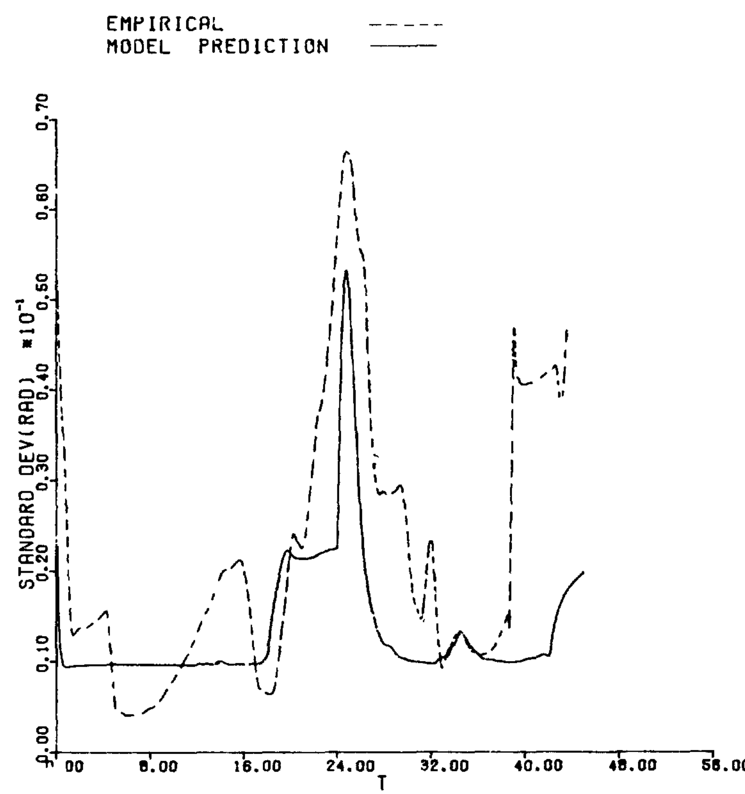


Figure 14. Elevation Simulation Result--Recon--6 seconds, 25 percent

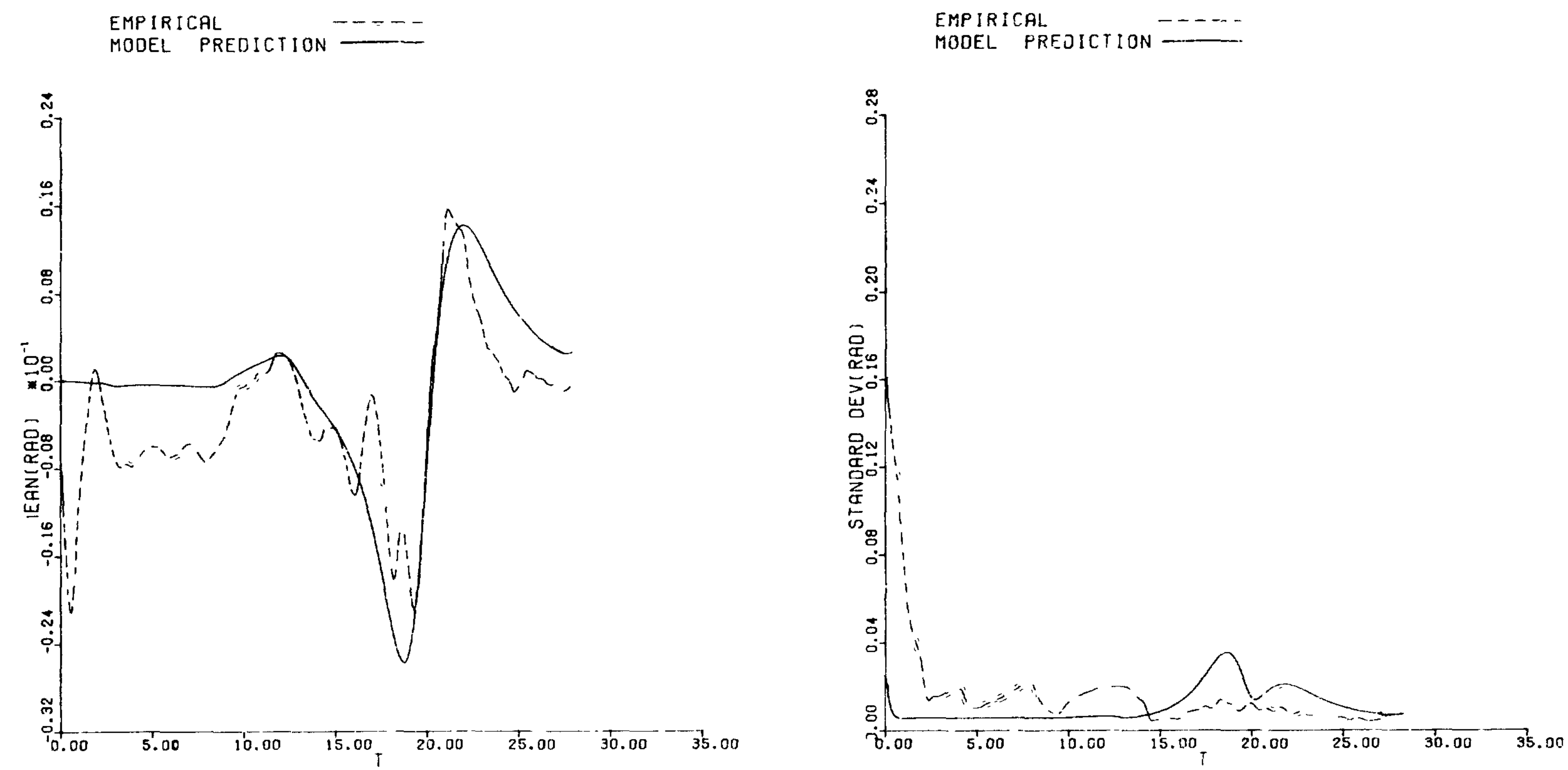


Figure 15. Azimuth Simulation Result--Weapon Delivery--No Blanking

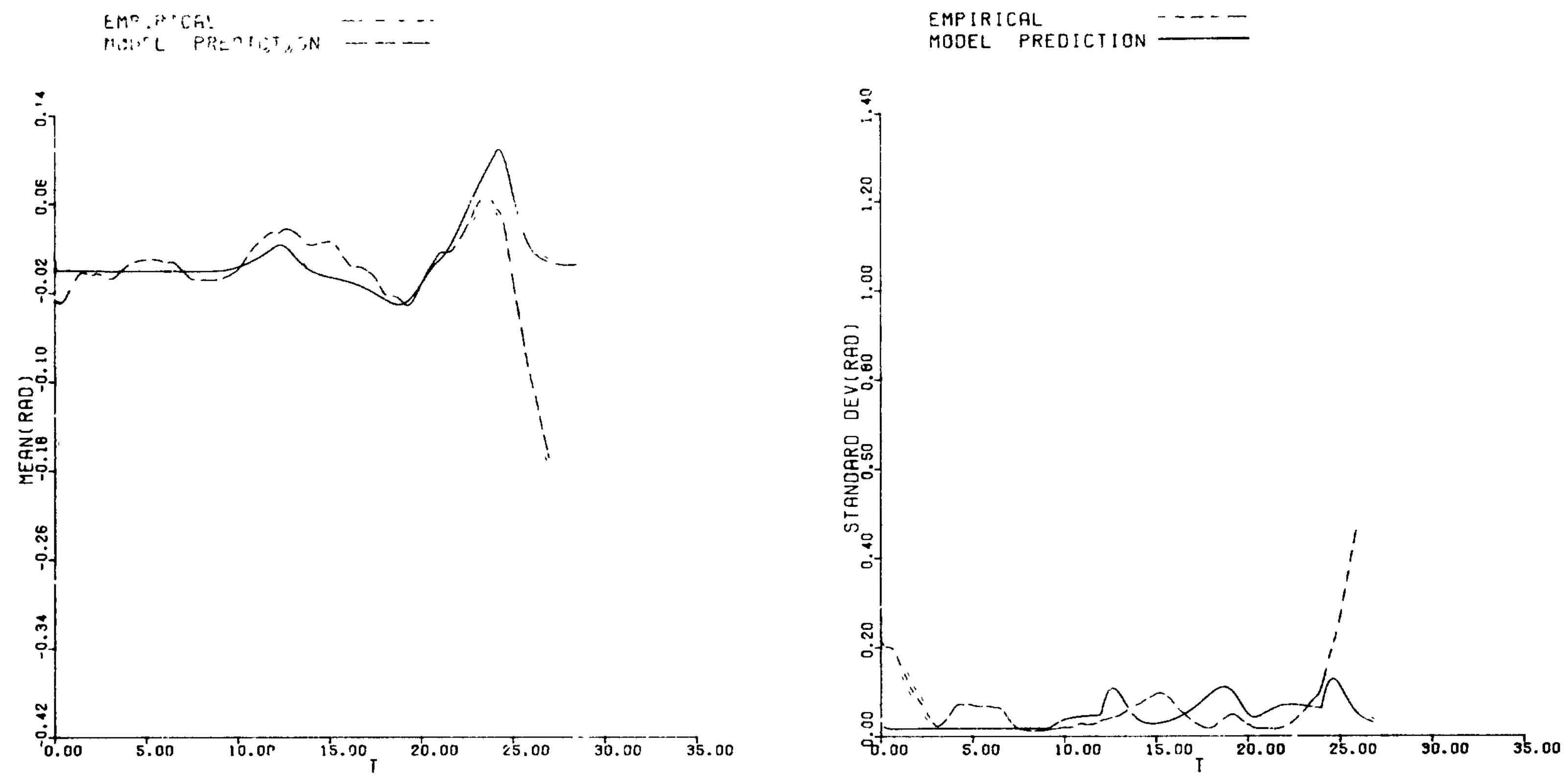


Figure 16. Azimuth Simulation Result--Weapon Delivery--3 seconds, 25 percent

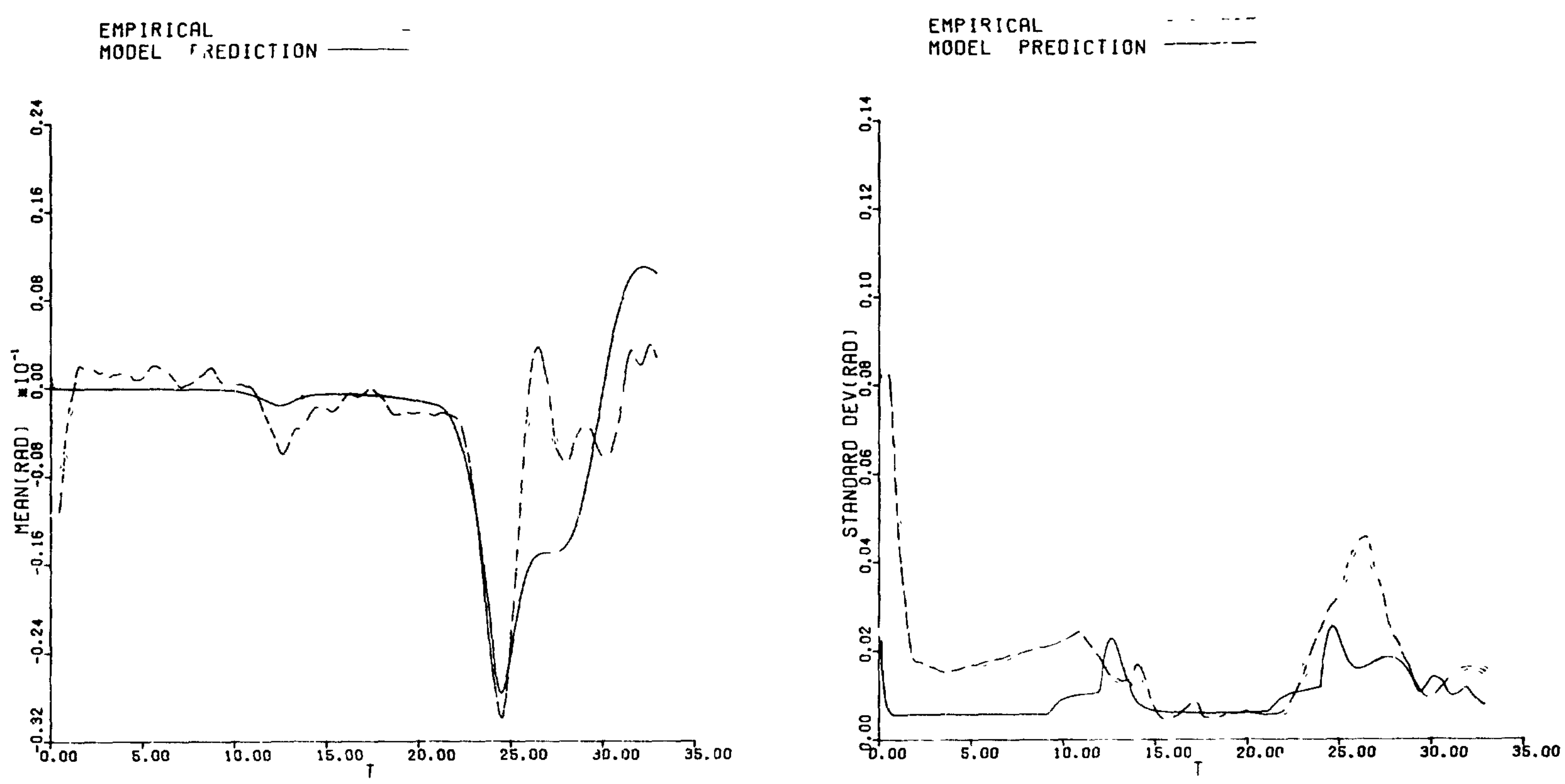


Figure 17. Azimuth Simulation Result--2 x 2 Flyby--3 seconds, 25 percent

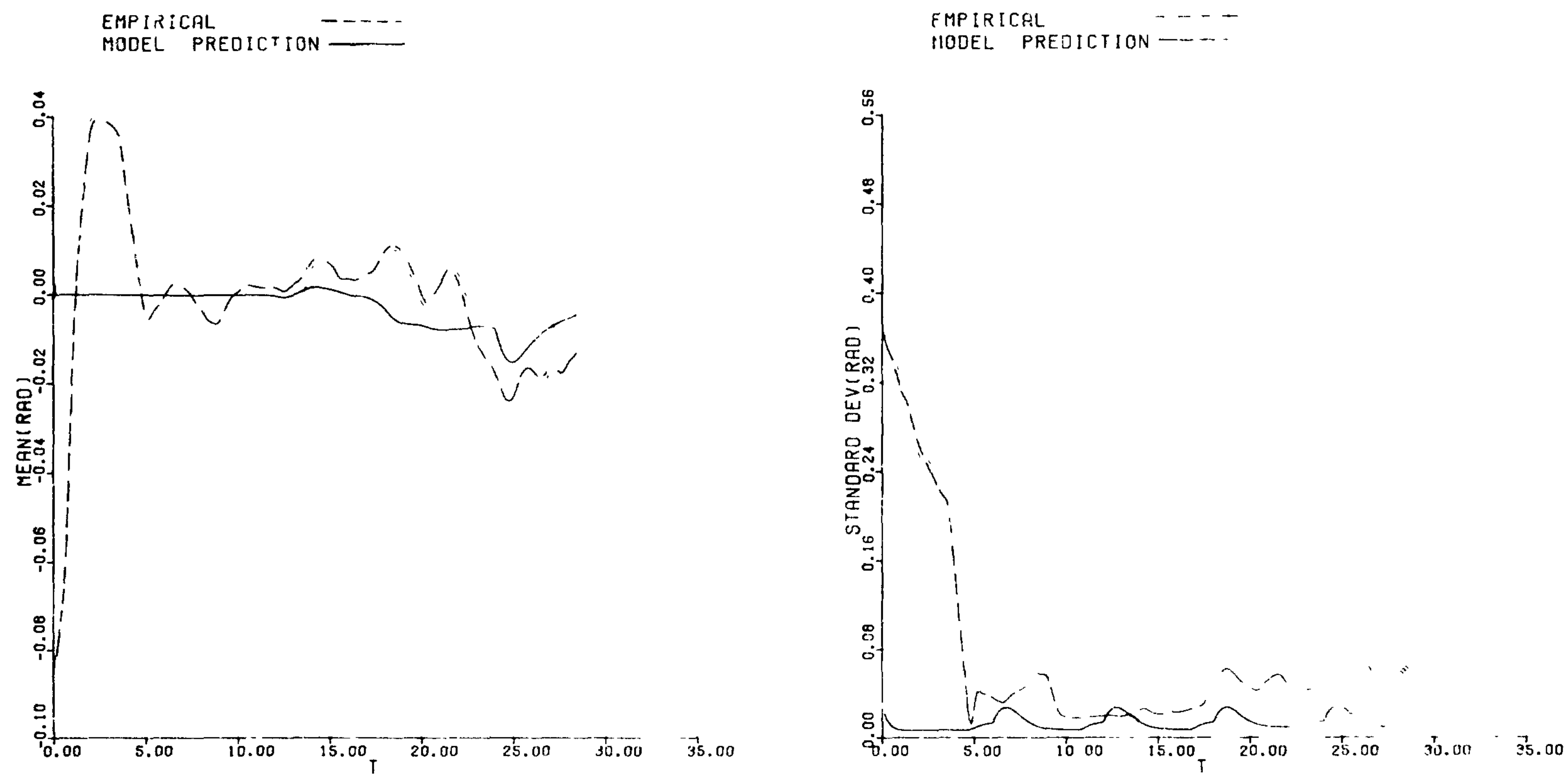


Figure 18. Azimuth Simulation Result--Recon--1.5 seconds, 25 percent

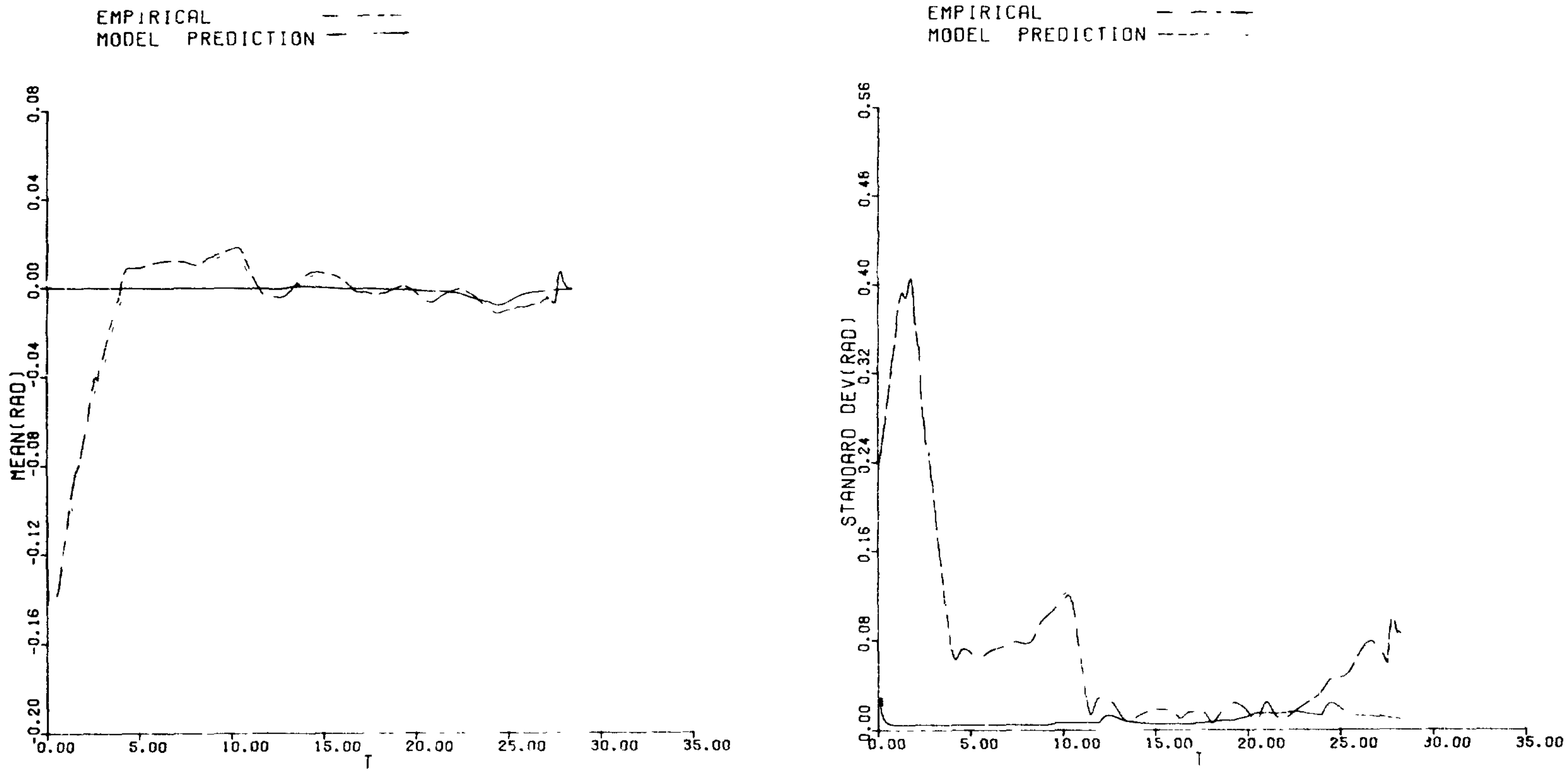
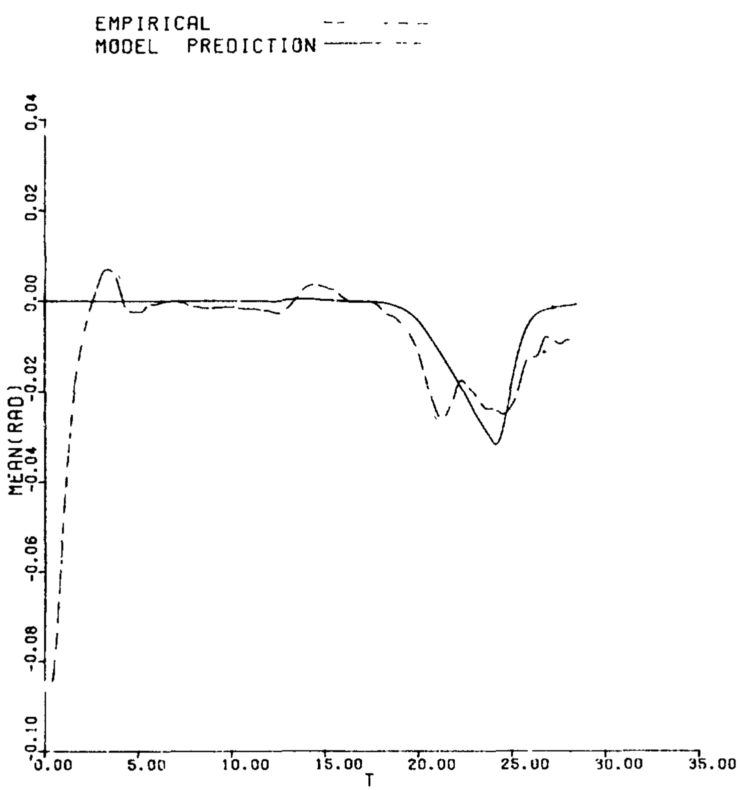


Figure 19. Azimuth Simulation Result--Recon--3 seconds, 25 percent



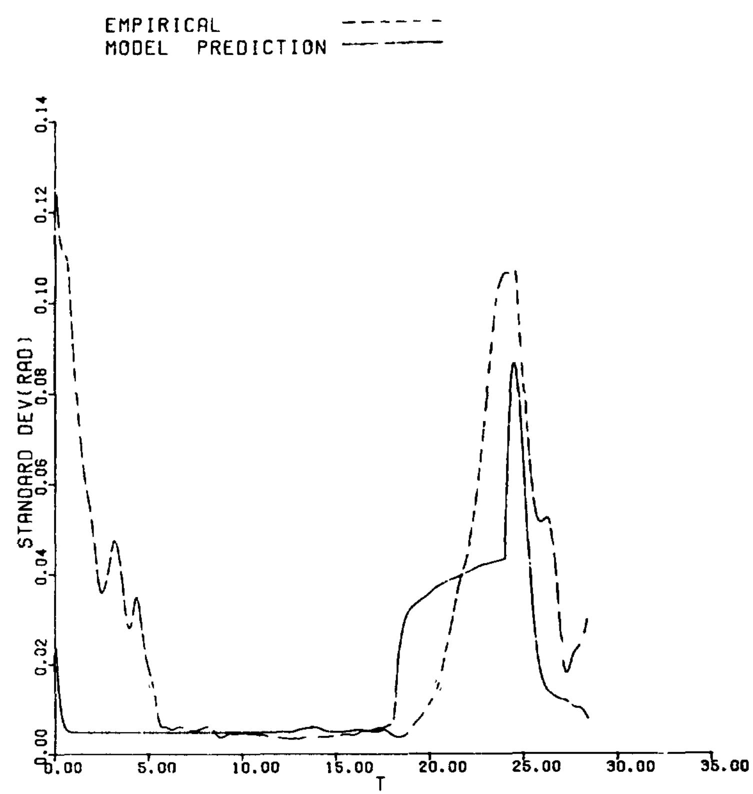


Figure 20. Azimuth Simulation Result--Recon--6 seconds, 25 percent

Section 9

CONCLUSIONS AND SUGGESTIONS FOR FURTHER STUDIES

Modeled as a linear feedback controller and a state reconstructor, the gunner was "parameterized" by the control gains and the estimation gains. These time-varying gains together with the noise covariances characterized the gunner's tracking performance. The time-varying gains directly reflect the gunner's tracking skill, tracking conditions, and his own psycho-physical parameters. Hence, the gains were modeled and identified from the experimental data.

The simulation results show very good model versus data matches. However, as indicated from Figures 6 to 20, some peak tracking errors predicted by the model tend to either overshoot or undershoot. This is due to the nonadaptive internal model of target motion in the current simulation [g(t) = 0]. In the observer formulation, the "local bandwidth" g(t) of the internal velocity directly enters the observer gain as [k(t)+g(t)]. The adaptive nature of the gunner's perception of target motion can be modeled by continuously "updating" the gain. In other words, by modeling the gain according to the gunner's perception of target acceleration, the overshoots can be eliminated, as shown in Figure 8 (k = 1.2).

The idea of simultaneous parameter identifications and state estimations has been explored recently in the literature of adaptive observers, for examples, see Nuyan and Carroll (1979) and Kudva and Narendra (1974). The Lyapunov function and the stability concept seem to be powerful tools for describing the adaptive nature of human's responses. For example, the observer gain can be adaptively adjusted to ensure only stable state estimations rather than asymptotic state reconstructions. This is a very interesting technique to be pursued.

APPENDIX A

THE COMPUTER SIMULATION PROGRAM

PROGRAM OWLSIMU

1. INPUT: ATTACH, TAPE 2
   Where TAPE 2 HAS AZIMUTH AND ELEVATION TARGET INFORMATION: T, AZ, AZD, AZDD, EL, ELD, ELDD

   TYPE IN BLANKING CONDITIONS:

   PERIOD = Blanking duration

   Icycle = Duty Cycle =

$$\frac{1}{\text{Percentage of time blanked}}$$

2. OUTPUT: MEAN TRACKING ERRORS AND STANDARD DEVIATIONS:
   AZERR, ELERR, AZSDM, ELSDM

REMARKS

This simulation program had been modified to a more general version which was then included in the engagement program P001. The modified version took the control constraints due to the physical limitations into consideration and had a general input blanking condition to replace the periodical one.

```
      PROGRAM OWLSIMU(INPUT,OUTPUT,TAPE2)
C
C     MODE2 BLANKING SIMULATION PROGRAM
C     INPUT(TAPE2)--TARGET INFORMATION:T,AZ,AZD,AZDD,EL,ELD,ELDD
C     INPUT(READ IN)--BLANKING STRATEGY:PERIOD,ICYCLE
C     OUTPUT--MEAN TRACKING ERRORS AND STANDARD DEVIATIONS :
C              ELERR,ELSDM,AZERR,AZSDM
C     ALL ANGLES ARE IN RADIANS
C
      COMMON//AR/DEL,N,N1,T,TAUK,TAUY,TAUC,TAU,PERIOD,TS(15),TE(15)
      COMMON//ARAZ/AZ,AZD,AZDD,MOAZ,MBAZ,ZAZ(3),Z1AZ(3),XAZ(3),X1AZ(9)
      COMMON//AREL/EL,ELD,ELDD,MOEL,MBEL,ZEL(3),Z1EL(3),XEL(3),X1EL(9)
      COMMON//AR/GUN,C,CD
      DIMENSION PAZ(8),PEL(8)
C
C     GUNNER PARAMETERS
      PAZ(1)=3
      PAZ(2)=[illegible].78
      PAZ(3)=1.2
      PAZ(4)=[illegible]2
      PAZ(5)=[illegible]3
      PAZ(6)=[illegible].53
      PAZ(7)=3
      PAZ(8)=1.2
      PEL(1)=2.99
      PEL(2)=[illegible].77
      PEL(3)=[illegible].48
      PEL(4)=[illegible]3
      PEL(5)=[illegible]9
      PEL(6)=1.3
      PEL(7)=2.99
      PEL(8)=[illegible].48
      TAUK=[illegible].3756
      TAUY=[illegible].32
      TAUC=[illegible].43
      TAU=[illegible].25
```

```
C
C     DATA AND INITIALIZATIONS
      DEL=.03
      N=3 $ N1=9
      OGUN=
      GUN=1
      MOAZ MBAZ MCEL-MBEL=0
C
C     READ IN BLANKING STRATEGY AND COMPUTE TIME INTERVALS
      PRINT ,*TYPE IN BLANK PERIOD,DUTY CYCLE
      READ ,PERIOD,ICYCLE
      DO 5 K=1,15
      TE(K) K ICYCLE PERIOD
      TS(K)=TE(K)-PERIOD
    5 CONTINUE
C
C     READ IN TARGET TRAJECTORY (TIME STEP . 3 SEC)
      DO 1  I=1,15
      READ(2,1 ) T,AZ,AZD,AZDD,EL,ELD,ELDD
      T=(I-1) DEL
C
C
      C=COS(GUN)
      C =-(SIN(GUN)) (GUN-OGUN)/DEL
      OGUN=GUN
      IF(T.LE.TS(1)) CALL OBSAZ(AZERR,AZSDM,PAZ)
      IF(T.LE.TS(1)) CALL OBSEL(ELERR,ELSDM,PEL)
      DO 5  K=1,6
      IF(T.GT.TS(K).AND.T.LE.TE(K))  CALL BKAZ (AZERR,AZSDM,PAZ)
      IF(T.GT.TS(K).AND.T.LE.TE(K))  CALL BKEL (ELERR,ELSDM,PEL)
      IF(T.GT.TE(K).AND.T.LE.TS(K+1)) CALL OBSAZ(AZERR,AZSDM,PAZ)
      IF(T.GT.TE(K).AND.T.LE.TS(K+1)) CALL OBSEL(ELERR,ELSDM,PEL)
    5 CONTINUE
      IF(T.GT.TS(15).AND.T.LE.TE(15)) CALL BKAZ(AZERR,AZSDM,PAZ)
      IF(T.GT.TS(15).AND.T.LE.TE(15)) CALL BKEL(ELERR,ELSDM,PEL)
      IF(T.GT.TE(15))  CALL BKAZ(AZERR,AZSDM,PAZ)
      IF(T.GT.TE(15))  CALL BKEL(ELERR,ELSDM,PEL)
    1 CONTINUE
    1 FORMAT(7G12.5)
      END
```

```
C
C     OBSAZ COMPUTES AZIMUTH ERRORS --NO BLANKING INTERVALS
C
      SUBROUTINE OBSAZ(AZERR,AZSDM,P)
      COMMON/VAR/DEL,N,N1,T,TAUK,TAUY,TAUC,TAL,PERIOD,TS(15),TE(15)
      COMMON/VARAZ/AZ,AZD,AZDD,MO,MB,Z(3),Z1(3),X(9),X1(9)
      COMMON/VAR/GLN,C,CD
      DIMENSION A(9),R1(3),W1(9),W2(9),DD(9),FHIT(9),VTM(9),PH(3)
      DIMENSION P(8)
      PC=P(8) EXP(-TAUK PERIOD)
      P(3)=PC+(P(8)-PC)*(1-EXP(-TAUC*MO DEL))
      P(1)=P(7) (1-EXP(-TAUY MO DEL))
      IF(T.LE.TS(1)) P(3)=P(8)
      IF(T.LE.TS(1)) P(1)=P(7)
      DO 1  J=1,N1
      DD(J)=FHIT(J)-VTM(J)=0
1     A(1)=
      A(1)=CD/C-1.28 C P(1)
      A(4)=C (1-1.28 P(2))
      A(7)=C 1.28 F(2)
      A(9)=-C P(3)
      CALL DSORT(N,A,DEL,W1,W2,10)
      DO 2  I=1,N
      R1(I)=1
      I3=I+N
      I2=I3+N
2     R1(I)=W2(I3)+W2(I2)
      IF(T.LT.T   1) GO TO 1
      Z(1)=Z(3)
      Z(2)=AZD
      DO 22 J=1,9
      X(J)=
22    CONTINUE
      X(1)=  .001
1     DO 35 I=1,N
      II=1
      PH(I)=
```

```
      DO 25 J=I,N1,N
      PH(I)=PH(I)+W1(J)*Z(II)
25    II=II+1
35    CONTINUE
      OESTV=Z(2)-Z(3)
      DO 40 I=1,N
      Z(I)=PH(I)+R1(I)*AZDD
40    CONTINUE
      AZERR=Z(1)
      V=P(4)+P(5)*(Z(2)-Z(3))*(Z(2)-Z(3))
      V=V+P(6)*(Z(2)-Z(3)-OESTV)*(Z(2)-Z(3)-OESTV)/(DEL*DEL)
      DD(1)=1.28*1.28*C*C*V/DEL
      DD(3)=-P(3)*DD(1)
      DD(7)=DD(3)
      DD(9)=P(3)*P(3)*DD(1)
      CALL MULT(W1,X,N,N1,PHIT,10)
      CALL MULT(W2,DD,N,N1,VTM,10)
      DO 42 I=1,9
      X(I)=PHIT(I)+VTM(I)
      X1(I)=X(I)
42    CONTINUE
      AZSDM=SQRT(X(1))
      DO 50 I=1,N
      Z1(I)=Z(I)
50    CONTINUE
      MO=MO+1
      ME=0
      RETURN
      END
C
C     BKAZ COMPUTES AZIMUTH ERRORS --BLANKING INTERVALS
C
      SUBROUTINE BKAZ(AZERR,AZSDM,P)
      COMMON/VAR/DEL,N,N1,T,TAUK,TAUY,TAUC,TAU,PERIOD,TS(15),TE(15)
      COMMON/VARAZ/AZ,AZD,AZDD,MO,ME,Z(3),Z1(3),X(9),X1(9)
      COMMON/VAR/GLN,C,CD
      DIMENSION AA(9),RR1(9),W3(9),W4(9),PPH(3),TEMP(3)
      DIMENSION DD(9),PHIT(9),VTM(9),P(8)
```

```
      DO 1? J=1,N1
      DD(J)=PHIT(J)-VIM(J)=?
1.    AA(J)=.
      AA(1)=DD/C
      AA(4)=C (1-1.28 F(2))
      AA(7)=C 1.28 F(2)
      AA(9)=-C*F(8) EXP(-TAUK*ME*DEL)
      CALL DSQRT(N,AA,DEL,W3,W4,1.)
      DO 2. I=1,N
      RR1(I)=?
      I3=I+N
      I2=I3+N
2.    RR1(I)=W4(I3)+W4(I2)
      DO 35 I=1,N
      II=1
      PPH(I)=.
      DO 25 J=I,N1,N
      PPH(I)=PPH(I)+W3(J)*Z1(.
25    II=II+1
35    CONTINUE
      DESTV=Z1(2)-Z1(3)
      DO 4. I=1,N
      TEMP(I)=-1.28 C*F(7)*Z(1)*EXP(-TAU*ME DEL)
      Z1(I)=PPH(I)+RR1(I)*AZDD+W4(I) TEMP(I)
4.    CONTINUE
      AZERR=Z1(1)
      V=P(4)+P(5) (Z1(2)-Z1(3))*(Z1(2)-Z1(3))
      V=V+P(6)*(Z1(2)-Z1(3)-DESTV) (Z1(2)-Z1(3)-DESTV)/(DEL*DEL)
      DD(1)=1.28*1.28*C*C*V/DEL
      DD(3)=-P(3) DD(1)
      DD(7)=DD(3)
      DD(9)=P(3) P(3)*DD(1)+?.1
      AA(1)=-1.28*F(7)*C
      CALL DSQRT(N,AA,DEL,W3,W4,1.)
      CALL MULT(W3,X1,N,N1,PHIT,1 )
      CALL MULT(W4,DD,N,N1,VIM,10)
      DO 42 I=1,9
      X1(I)=PHIT(I)+VIM(I)
```

```
      X(I)=X1(I)
 40   CONTINUE
      AZSDM=SQRT(X1(1))
      DO 5  I=1,N
      DO 45 K=1,15
      IF(T.EQ.TE(K))  Z(I)=Z1(I)
 45   CONTINUE
 50   CONTINUE
      MB=MJ+1
      MO=L
      RETURN
      END
C
C     OESEL COMPUTE. ELEVATION ERRORS --NO BLANKING INTERVALS
C
      SUBROUTINE OESEL(ELERP,ELSDM,P)
      COMMON/VAR/DEL,N,N1,T,TAUK,TAUY,TAUC,TAL,PERIOD,TS(15),TE(15)
      COMMON/VAREL/EL,ELD,ELDD,MO,ML,Z(3),Z1(3),X(9),X1(9)
      COMMON/VAR/GUN,C,CD
      DIMENSION A(9),R1(3),W1(9),W2(9),DD(9),PHIT(9),VIM(9),PH(3)
      DIMENSION P(8)
      PC=P(6) EXP(-TAUK PERIOD)
      P(3)=PC+(P(8)-PC) (1-EXP(-TAUC MO DEL))
      P(1)=P(7) (1-EXP(-TAUY MO DEL))
      IF(T.LE.TS(1)) P(3)=P(8)
      IF(T.LE.TS(1)) P(1)=P(7)
      DO 10 J=1,N1
      DD(J)=PHIT(J) VIM(J)=0
 10   A(J)=
      A(1)=-1.34 P(1)
      A(4)=1-1.34 P(2)
      A(7)=1.34 P(2)
      A(9)=-P(3)
      CALL LSQRT(N,A,DEL,W1,W2,10)
      DO 20 I=1,N
      R1(I)=J
      I3=I+N
      I2=I3+N
```

```
2.      R1(I)=W2(I3)+W2(I2)
        IF(I.GT.C.U31) GO TO 1
        Z(1)=Z(3)=
        Z(2)=ELD
        DO 22 J=1,9
        X(J)=.
22      CONTINUE
        X(1)=..]01
1       DO 35 I=1,N
        II=1
        PH(I)=0
        DO 25 J=I,N1,N
        PH(I)=PH(I)+W1(J)*Z(II)
25      II=II+1
35      CONTINUE
        DESIV=Z(2)-Z(3)
        DO 4. I=1,N
        Z I)=EH(I)+R1(I)*ELDD
4.      CONTINUE
        ELE2R=Z(1)
        V=P(4)+P(5)*(Z(2)-Z(3))*(Z(2)-Z(3))
        V=V+P(6)*(Z(2)-Z(3)-DESIV)*(Z(2)-Z(3)-DESIV)/(DEL*DEL)
        DD(1)=1.34 1.34*V/DEL
        DD(3)=-P(3)*DD(1)
        DD(7)=DD(3)
        DD(9)=P(3)*P(3)*DD(1)
        CALL MULT(W1,X,N,N1,PHIT,10)
        CALL MULT(W2,DD,N,N1,VTM,10)
        DO 42 I=1,9
        X(I)=PHIT(I)+VTM(I)
        X1(I)=X(I)
42      CONTINUE
        ELSDM=SQRT(X(1))
        DO 5. I=1,N
        Z1(I)=Z(I)
5.      CONTINUE
        MO=MO+1
        ME=
```

```
      GUN=EL-ELERR
      RETURN
      END
C
C     ELBK COMPUTES ELEVATION ERRORS --BLANKING INTERVALS
C
      SUBROUTINE EKEL(ELERR,ELSDM,P)
      COMMON/VAR/DEL,N,N1,I,TAUK,TAUY,TAUC,TAL,PERIOD,TS(15),TE(15)
      COMMON/VAREL/EL,ELD,ELDD,MO,MB Z(3),Z1(3),X(9),X1(9)
      COMMON/VAR/GUN,C,CO
      DIMENSION AA(9),RR1(9),W3(9),W4(9),PPH(3),TEMP(3)
      DIMENSION DD(9),PHIT(9),VTM(9),P(8)
      DO 1) J=1,N1
      DD(J)=PHIT(J)=VTM(J)=?
1.    AA(J)=)
      AA(4)=1-1.34*P(2)
      AA(7)=1.34*P(2)
      AA(9)=-P(8) EXP(-MB*DEL*TAUK)
      CALL DSORT(N,AA,DEL,W3,W4,1 )
      DO 2) I=1,N
      RR1(I)=)
      I3=I+N
      I2=I3+N
2.    RR1(I)=W4(I3)+W4(I2)
      DO 35 I=1,N
      II=1
      PPH(I)=)
      DO 25 J=I,N1,N
      PPH(I)=PPH(I)+W3(J)*Z1(II)
25    II=II+1
35    CONTINUE
      DESTV=Z1(2)-Z1(3)
      DO 4) I=1,N
      TEMP(I)=-1.34 P(7)*Z(1)*EXP(-TAU MB DEL)
      Z1(I)=PPH(I)+RR1(I)*ELDD+W4(I)*TEMP(I)
4.    CONTINUE
      ELERR=Z1(1)
      V=P(4)+P(5) (Z1(2)-Z1(3))*(Z1(2)-Z1(3))
```

```
      V=V+P(6)*(Z1(2)-Z1(3)-OESTV)*(Z1(2)-Z1(3)-OESTV)/(DEL*DEL)
      DD(1)=1.34 1.34*V/DEL
      DD(3)=-P(3) DD(1)
      DD(7)=DD(3)
      DD(9)=P(3) P(7)*DD(1)+P.1
      AA(1)=-1.34 P(7)
      CALL DSORT(N,AA,DEL,W3,W4,1.)
      CALL MULT(W3,X1,N,N1,PHIT,1 )
      CALL MULT(W4 DD,N,N1,VTM,10)
      DO 42 I=1,9
      X1(I)=PHIT(I)+VTM(I)
      X(I)=X1(I)
   42 CONTINUE
      ELSOM=SQRT(X1(1))
      DO 50 I=1,N
      DO 45 K=1,15
      IF(T.EQ.TE(K)) Z(I)=Z1(I)
   45 CONTINUE
   50 CONTINUE
      ML=M3+1
      MO=0
      LUN=EL-ELERR
      RETURN
      END
C
C     MULT----MATRIX MULTIPLICATIONS----
C     IF MR=1, H=E F
C     IF NOT(E.G.MR 1.),H=E F*E'
C
      SUBROUTINE MULT(E,F,L,L1,H,MR)
      DIMENSION E(L1),F(L1),G(9),H(L1)
      DO 1. I=1,L
      II=1
      DO 1. K=1,L
      TEMP=0
      DO 5 J=I,L1,L
      TEMP=TEMP+E(J) F(II)
    5 II=II+1
```

```
      KK=(K-1)*L+I
      H(KK)=TEMP
1.    G(KK)=TEMP
      IF(MR.EQ.1) RETURN
      DO 2. I=1,L
      DO 2. K=1,L
      TEMP=
      II=K
      DO 15 J=I,L1,L
      TEMP=TEMP+G(J)*F(II)
15    II=II+L
      KK=(K-1)*L+I
2.    H(KK)=TEMP
      L2=L-1
      DO 3. I=1,L2
      L3=I+1
      DO 3. J=L3,L
      K1=(I-1)*L+J
      K2=(J-1)*L+I
3.    H(K1)=H(K2)
      END
C
C     USCRT---TRANSITION MATRIX---
C     EA=EXP(A*DEL);EAINT=INTEGRAL OF EXP(A DEL)
C
      SUBROUTINE USCRT(NDIM,A,DEL,EA,EAINT,NT)
      DIMENSION A(1),EA(1),EAINT(1),COEF(3.)
      NDIM1=NDIM+1
      NN=NDIM*NDIM
      NTM1=NT-1
      COEF(NT)=1
      DO 1. I=1,NTM1
      II=NT-I
1.    COEF(II)=DEL*COEF(II+1)/FLOAT(I)
C     NT MUST BE AT LEAST 3
      CALL DIAG(NDIM,EAINT,A,COEF(1),COEF(2))
      DO 6. L=3,NT
      CALL MULT(A,EAINT,NDIM,NN,EA,1)
```

```
      IF(L.EQ.NT)GC TO 70
60    CALL DIAG(NDIM,EAINT,EA,1.0,COEF(L))
70    DO 81 II=1,NN,NDIM1
      EA(II)=EA(II)+1.0
80    CONTINUE
      END
C
C     DIAG---MATRIX ADDITION---
C
      SUBROUTINE DIAG(NDIM,A,B,C1,C2)
      DIMENSION A(1),B(1)
      NDIM1=NDIM+1
      NN=NDIM NDIM
      NM1=NDIM-1
      II=1
      IF(C1.EQ.1.0) GO TO 10
      DO 5 J=1,NN,NDIM
      K=J+NM1
      DO 4 I=J,K
4     A(I)=C1*B(I)
      A(II)=A(II)+C2
5     II=II+NDIM1
      RETURN
10    DO 7 J=1,NN,NDIM
      K=J+NM1
      DO 6 I=J,K
6     A(I)=B(I)
      A(II)=A(II)+C2
7     II=II+NDIM1
      RETURN
      END
```

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