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ON THE INTERNAL TARGET MODEL IN A TRACKING TASK

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SUMMARY

In this paper, the problem of selecting a suitable internal target model for a human operator in a tracking task is investigated. The results are analyzed for a target executing a straight and level constant velocity fly-by. The internal target model is formulated in the Cartesian coordinates. The geometry of the perceived tracking error and error rate makes the formulation a nonlinear filtering problem in which the fly-by parameters are to be estimated. Although no attempt is made to match experimental data, the qualitative features of the results capture the important aspects of the empirical findings. For instance, the approach leads to a mean tracking error response which is asymmetric about crossover. The asymmetry of the mean appears to be traceable to the fundamental observability conditions arising from the formulation. As crossover is neared, the system becomes more observable and, thus, the target position and velocity estimates improve dramatically. Furthermore, the constant fly-by parameter is learned right around crossover. Given the internal model for a fly-by, this allows the gunner to estimate future position and velocity much better and, thereby reduce overshoot after crossover.

I. INTRODUCTION

The modelling of a human operator's information processing capability and control strategy in a nonstationary target tracking test has been the topic of several investigations over the years [1]-[7]. The understanding of this facet of human behavior is especially critical in manned anti-aircraft artillery (AAA) systems since the human plays a central role either as a decision maker in an automatic mode or as a feedback controller in a manual tracking mode. Therefore, the development of appropriate models mimicking the human functions of perception, decision and control in an AAA task is essential for successful manned-threat quantification predictions.

Various human operator models have been proposed for inclusion in simulations of AAA weapon systems. In the early Franklin study [1], it was assumed that the tracking interval consists of three time invariant partitions corresponding to pre-crossover, crossover and post-crossover intervals. The authors indicate that this assumption is justifiable since the nature of the tracking test forces the operator to adopt different tracking strategies in order to prepare for high angular accelerations that will occur at crossover, to track the target at crossover, and to call off a tracking mission after crossover. The human operator model is then obtained through an impulse response matching procedure for the three intervals. While the model developed accounted for the human operator behavior up to crossover, the data matching performance was poor after crossover. Several speculations were cited for possible explanation of the post-crossover deviation such as nonsteady behavior, learning effects, nonlinear transfer behavior and cross-coupling effects.

In the Eglin study [2], the human operator model was developed using the classical control theory approach. This model contained two time varying nonlinear representations for the human operator; one for pre-crossover and the other for post-crossover tracking. Values for the human operator parameters were selected from the manual control literature and the other gain coefficients of the model were adjusted to provide a good match to tracking data. While the data matching performance of the Eglin model was satisfactory for the particular set of simulations, the Eglin model contained certain inherent limitations. For instance, the model did not predict error variance, since it did not account for the human operator variability. Moreover, this model did not explicitly account for human's adaptation to changing gun dynamics.

The use of the optimal control model for the human operator [3] resulted in predictions which were in reasonable agreement with the experimental data in the Vulcan and other studies [4]-[6]. Optimal control model provided estimates not only for the means of the variables of interest but also for the corresponding variances. In the Vulcan model, the internal model for the target trajectory was based on either a piecewise constant angular velocity (or acceleration). Furthermore, it was postulated that the human did no know the value of the incremental step change in the target's angular velocity (or acceleration). While the model predictions were improved over the previous applications, certain asymmetric and structural trends in the human response data could not be predicted.

This asymmetry is the experimental data was predicted by assuming a first order model with a variable bandwidth for the target angular velocity [7]. The bandwidth parameter was continually updated using a specific identification scheme. In this paper, we present a different modification of the optimal control model which also predicts the asymmetry in the tracking data. Here, the target dynamics (constant velocity, straight fly-by) are exactly formulated in the rectangular coordinates and the specific geometry arising from the gunner's perception in the spherical coordinates are specified. A nonlinear filter is then employed by the gunner to estimate the target parameters. The difference between this method and the one given in [7] is that the internal target model here is dependent on the class of target maneuvers. For instance, if a different set of target trajectories are to be studied (e.g. zigzag maneuvers), then the internal model here would be changed to reflect the change in the target dynamics. In contrast, the internal target model in [7] for the zigzag maneuver would be the same as the constant fly-by case.

II. INTERNAL TARGET MODEL

The problem geometry considered here is given in Figure 1.

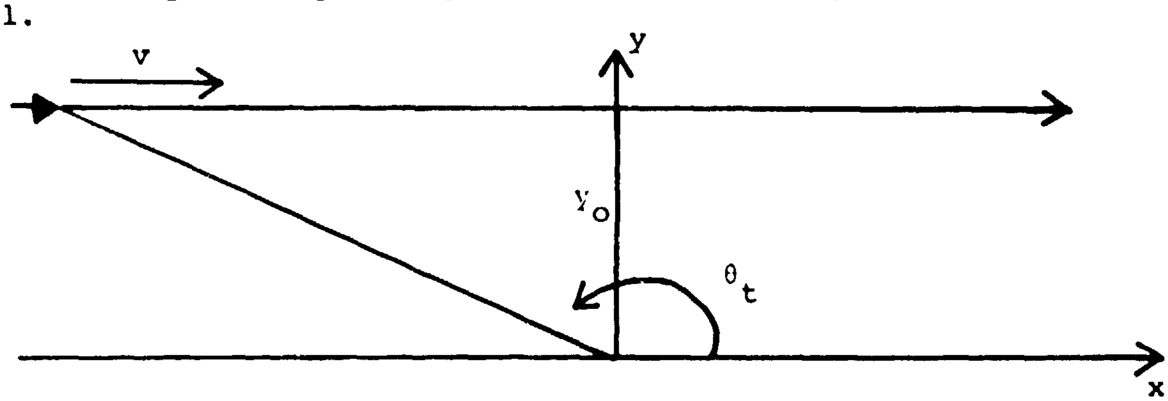

Figure 1. Problem Geometry

The target trajectory is from a class of constant velocity straight and level fly-bys. The constant target velocity, v, and the range at crossover, y_o, are unknown to the gunner. The human controls the rate of the sight angle, θ_s, in order to minimize the observed tracking error, $\theta_T-\theta_S$, where θ_T is the target azimuth. Defining the state variables by

$$x_1=\cot(\theta_T) \quad x_2=v/y_o \quad x_3=\dot{\theta}_T \quad x_4=\theta_T-\theta_S \quad x_5=u \tag{1}$$

we get the following internal model for the target dynamics:

$$\dot{x}_1 = x_2 \quad \dot{x}_2 = 0 \quad \dot{x}_3 = 2x_1 x_3^2 \quad \dot{x}_4 = x_3 - x_5 \quad \dot{x}_5 = \dot{u} + v_u \tag{2}$$

where u is the gunner control and v_u is the operator motor noise. The gunner perceives the tracking error and derives the rate of this error so that the measurement equations become:

$$y_1 = x_4 + v_e \qquad y_2 = x_3 - x_5 + v_{\dot{e}} \tag{3}$$

We have utilized an extended Kalman filter for the gunner's estimator based on equations (2) and (3). We are postulating that the gunner knows that the target is executing a straight and level fly-by. However, he does not know the target's velocity and range. As can be seen from Figures 2 and 3, the gunner's estimate of target position (Θ_T) and velocity (v/y_o) improve dramatically as crossover is neared. This behavior is expected due to the fundamental observability conditions arising from the problem geometry. The learning of the constant fly-by parameters right around crossover is the main reason for the asymmetric mean tracking response shown in Figure 4. Figures 4 and 5 are the ensemble average of 15 model runs. As can be seen from Figure 5, the standard deviation of the tracking error also captures the trends of the empirical findings in [7]. We have used nominal model parameters in these runs. The steady-state control gains were used for the linear model utilizing the current estimates for x_1 and x_3 so that

$$\dot{u} = (10+2\hat{x}_1\hat{x}_3)\hat{x}_3+50\hat{x}_4-10\hat{u} \tag{4}$$

In our formulation $-2x_1x_3$ corresponds to the bandwidth in [7].

III. CONCLUSIONS

Another modification in the optimal control model for an AAA gunner is presented. Although no attempt is made to match experimental data, the qualitative features of the results predict the important aspects of empirical findings such as asymmetric mean tracking error. Since the developed internal target model is dependent on the specific class of target maneuvers, the approach of this paper may be useful in modelling the decision making process of a gunner in identifying a specific target maneuver out of a possible number of target trajectory classes.

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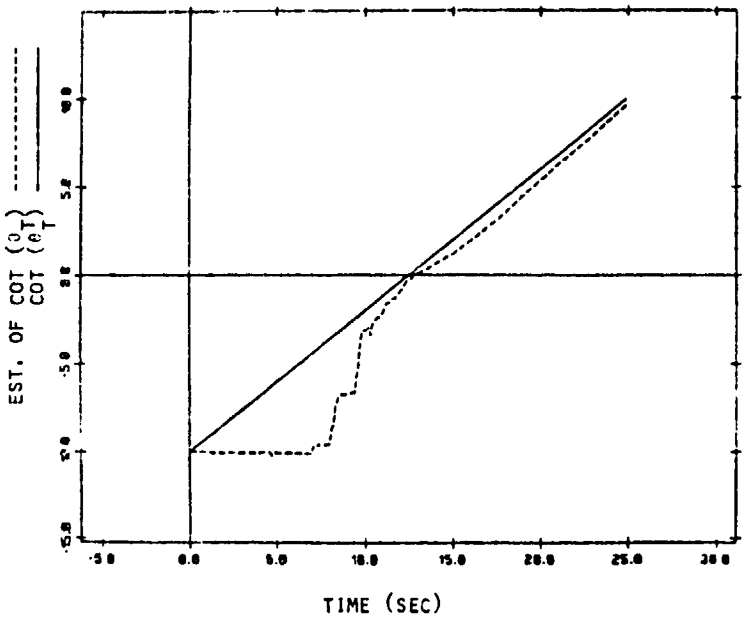

Figure 2. Estimation of Target Azimuth Angle

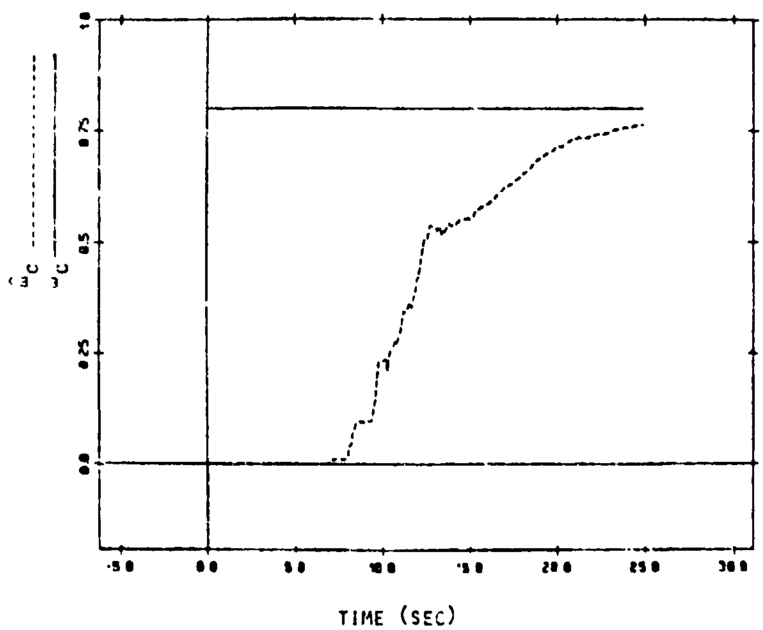

Figure 3. Estimation of Target Crossover Angular Velocity

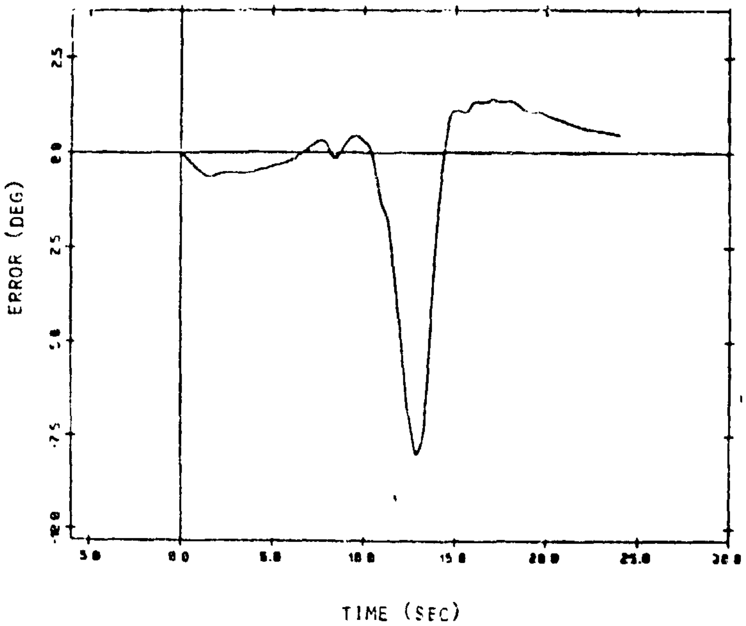

Figure 4. Ensemble Mean of Tracking Error (N=15)

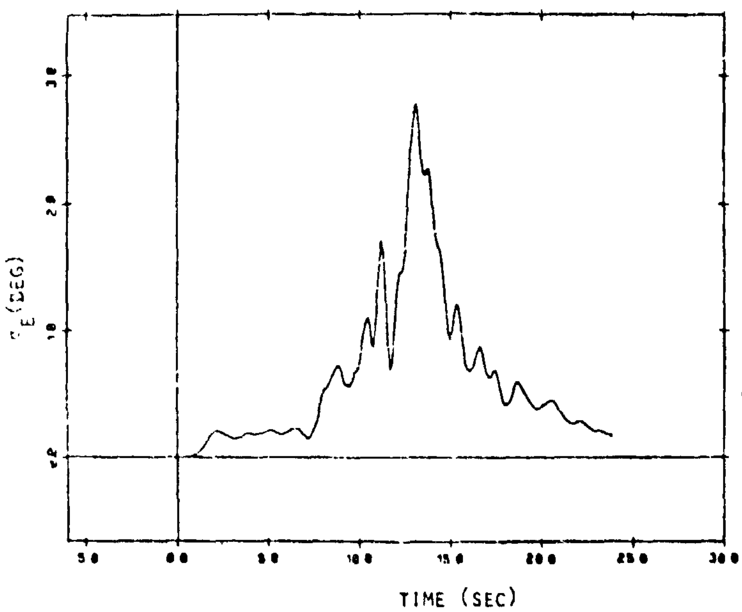

Figure 5. Ensemble Mean of Tracking Error S.D. (N=15)