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A TRACKING ALGORITHM USING BEARING ONLY.(U)

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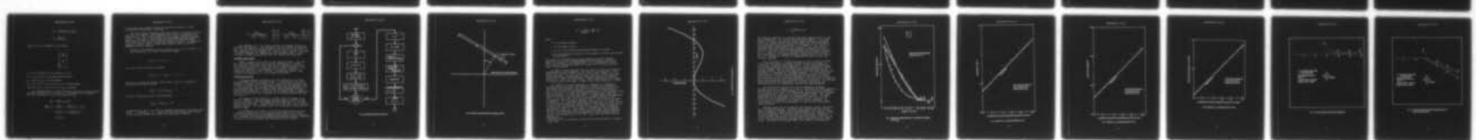

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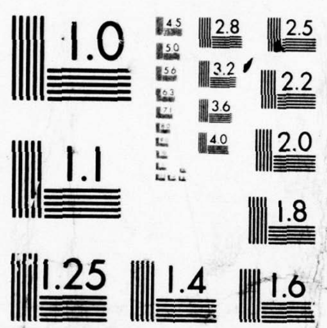

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NSWC TECHNICAL REPORT

WHITE OAK LABORATORY

A TRACKING ALGORITHM USING BEARING ONLY

BY
Thomas B. Ballard
R. Scott Hebbert

20 OCTOBER 1975

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A Kalman filter for tracking a moving acoustic radiator by means of angle of arrival information is developed. The Kalman equations are linearized about the measured angles rather than the state estimate in order to free the filters from dependence on an initial state estimate. Performance of the tracking algorithm is evaluated with Monte Carlo simulations.

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Preface 20 October 1975

This report is the first of two treating the problem of doppler/bearing tracking of a moving target by means of a single directional sensor. A method of estimating target track parameters by processing bearing information only is developed. A forthcoming report will address the problem of combining doppler and bearing information.

This work was performed under task AIR A370-3700/6W11-121-711.

Edward C. Whitman

EDWARD C. WHITMAN
By direction

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A TRACKING ALGORITHM USING BEARING ONLY

INTRODUCTION

It is possible to track a moving acoustic radiator by means of a single passive sensor which measures angle of arrival and frequency of the radiated signal. Although in theory a very modest number of independent angle and frequency measurements are required in order to determine the target track, in practice the effects of noise make it highly desirable to process as many observations as possible. The best estimate of target track is then determined by means of a least squares or maximum likelihood fit to the observations. The process of fitting the estimated track to the data may be carried out by batch processing a large block of observations simultaneously or by an iterative scheme such as the Kalman filter which processes each new observation as it is received.

The equations which relate the target track parameters to the frequency and angle of arrival of the signal received at the sensor are non-linear. This considerably complicates the process of performing a least squares or maximum likelihood fit. Generally, rather than perform an exhaustive multi-dimensional search for the estimate that yields the best fit, the equations are linearized about some reference solution and solved with linear theory. This technique is used in both the batch and iterative formulations. In either case the validity of the final result is dependent upon whether or not the reference solution was sufficiently accurate so that convergence to a true minimum error solution actually occurred rather than divergence or convergence to a false minimum. As the observations become more noisy this problem becomes accentuated.

The approach taken in this paper is that the overall tracking problem can be divided into two parts. Information about the target track can first be extracted from angle of arrival observations, and then as a second step frequency observations can be used to complete the target track estimate. Splitting the solution into two parts simplifies the problems associated with linearization and initialization by reducing the number of state parameters under consideration at one time and also makes it possible to employ different techniques in solving the two problems. The specific problem considered in this paper is the processing of angle of arrival observations by a bearing tracker to yield an estimate of target track parameters. The processing of frequency observations will be considered in a later paper.

The bearing tracker employs an extended Kalman filter formulated in such a way that the filter is linear in two of the three state variables and non-linear in the remaining one. A conventional linearization procedure is used with respect to this third variable. However, instead of assuming or in some manner deriving a single point about which to linearize, a family of solutions is carried out in parallel so that under all circumstances one of the solutions lies in the region where the assumptions used in the linearization procedure are valid. Thus the Kalman filter requires no apriori knowledge in order to begin processing observations.

STATE DEFINITION

To define the path of a target moving in straightline unaccelerated motion, a four dimensional state is required. A tracker using bearings only is incapable of providing all four necessary parameters; at most three can be determined. The state representation chosen for use in the bearing tracker is:

$$X = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} -\frac{V}{R} t_o \\ \frac{V}{R} \\ \beta \end{bmatrix}$$

where V is the target velocity

R is the range at closest approach

t_o is the time of closest approach referenced to initial acquisition

β is the bearing from the sensor to the target at closest approach.

The geometry is shown in Figure 1.

If additional information concerning V or R derived either from apriori information or from processing doppler information can be provided, then the target path is completely determined. Lacking such information, the tracker output is a family of parallel paths bounded on one side by the sensor and on the other by the maximum speed capability of the target.

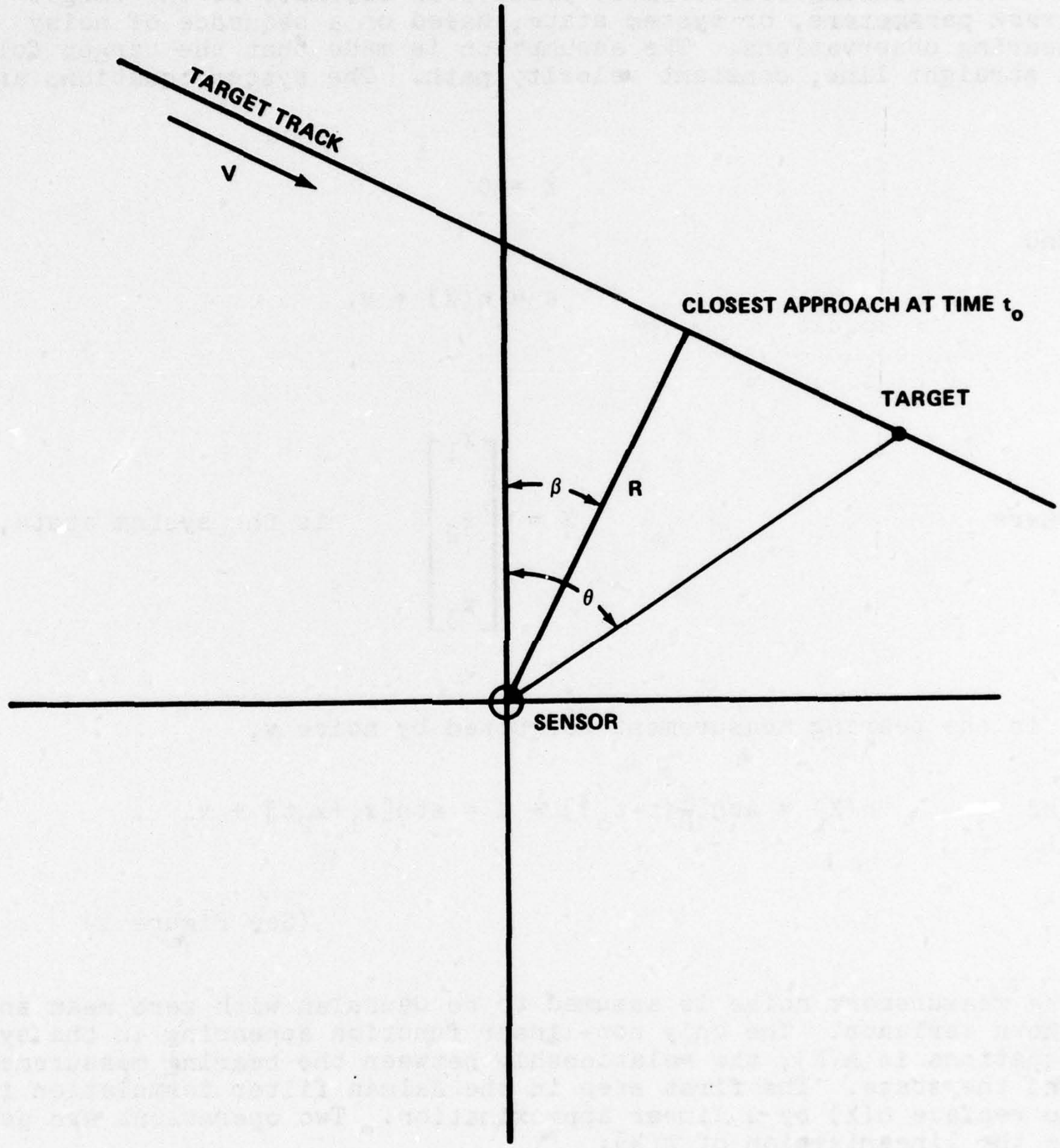

FIG. 1 TARGET TRACK GEOMETRY

KALMAN FILTER

The bearing tracker must produce an estimate of the target track parameters, or system state, based on a sequence of noisy bearing observations. The assumption is made that the target follows a straight line, constant velocity path. The system equations are:

$$\dot{X} = 0$$

and

$$\theta = h(X) + v.$$

Where $X = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$ is the system state,

θ is the bearing measurement corrupted by noise v,

and $h(X) = \operatorname{atn}[\frac{V}{R}(t-t_o)] + \beta = \operatorname{atn}[x_1+x_2t] + x_3$.

(See Figure 1)

The measurement noise is assumed to be Gaussian with zero mean and known variance. The only non-linear function appearing in the system equations is h(X), the relationship between the bearing measurement and the state. The first step in the Kalman filter formulation is to replace h(X) by a linear approximation. Two operations are performed in the linearization of h(X):

1. A non-linear function, the tangent, is applied to the bearing observations.

2. The resulting function is linearized about an assumed value of x_3, the bearing at closest approach.

Instead of initially committing the solution to a single assumed value of x_3, which may later turn out to be erroneous, the problem is worked in parallel assuming a family of values of x_3. This removes the necessity of an initial state estimate. Later as the solution unfolds it is possible to reject all but the closest assumed value of x_3.

The linearization proceeds as follows:

$$\theta = \text{atn}(x_1+x_2t) + x_3 + v.$$

Let $\{\gamma\}_i$ $i = 1, \ldots\ldots, n$ be a family of equally spaced reference angles between 0 and π. The periodicity of the tangent function introduced in the next step makes it unnecessary for γ to assume values between π and 2π.

$$\text{Let } y_i = \tan(\theta-\gamma_i) = \tan[\text{atn}(x_1+x_2t)$$

$$+ (x_3-\gamma_i) + v].$$

The linear approximation to this equation is

$$y_i = M_iX_i+v_i$$

where

$$X_i^T = [x_1, x_2, x_3-\gamma_i]$$

$$M_i = [\frac{\partial y_i}{\partial x_1}, \frac{\partial y_i}{\partial x_2}, \frac{\partial y_i}{\partial x_3}]$$

v_i, the noise, is amplified by the non-linear tangent function so that to first order

$$\frac{\text{var}(v_i)}{\text{var}(v)} = (\frac{\partial y_i}{\partial v})^2 \quad .$$

Then

$$M_i = \left[\frac{1+y_i^2}{1+(x_1+x_2t)^2} , \frac{t(1+y_i^2)}{1+(x_1+x_2t)^2} , 1+y_i^2 \right]$$

and

$$\frac{var(v_i)}{var(v)} = (1+y_i^2)^2 .$$

The measurement matrix can be simplified as a result of two further assumptions:

1) Assume $x_3 - \gamma_i$ is small for the γ_i closest to x_3. This is true if n has been chosen sufficiently large.

2) Assume that the input bearing measurements have previously been averaged over a sufficiently long period of time so that their variation due to noise is not excessive.

Under these assumptions:

$$y_i = \tan[\text{atn}(x_1+x_2t) + (x_3-\gamma_i) + v]$$

$$\approx (x_1+x_2t) .$$

Substitution of this result into the previously derived expression for M_i yields the approximation

$$M_i = [1, t, 1+y_i^2] .$$

This simplification is significant because it frees the Kalman filter equations from any dependence upon the estimated state or past measurements and makes the equations dependent only upon the present measurement.

The Kalman estimator, shown for clarity in continuous form, is

$$\dot{\hat{X}}_i = Z_i^{-1} M_i R_i^{-1} (y_i - M_i \hat{X}_i)$$

$$\dot{Z}_i = M_i^T R_i^{-1} M_i \ .$$

where $\hat{X}_i$ is the estimate of the state,

$$\begin{bmatrix} -\frac{V}{R} t_o \\ \frac{V}{R} \\ \beta - \gamma_i \end{bmatrix}$$

Z_i is the inverse of the covariance of $\hat{X}_i$

$M_i = [1, t, 1+y_i^2]$ is the measurement matrix

$y_i = \tan(\theta - \gamma_i)$ is the measurement

$R_i = R_\theta (1+y_i^2)^2$ is the variance of the measurement

where R_θ is the variance of the input bearings.

The implementation of these equations requires an initial state estimate and associated covariance. To avoid this we transform the first equation to one in the variable $Z_i \hat{X}_i$.

$$Z_i \dot{\hat{X}}_i = M_i^T R_i^{-1} (y_i - M_i \hat{X}_i)$$

$$\frac{d}{dt}(Z_i \hat{X}_i) = M_i^T R_i^{-1} y_i - M_i^T R_i^{-1} M_i \hat{X}_i + \dot{Z}_i \hat{X}_i$$

$$= M_i^T R_i^{-1} y_i + (\dot{Z} - M_i^T R_i^{-1} M_i) \hat{X}_i$$

$$= M_i^T R_i^{-1} y_i \ .$$

At any time that a state estimate is required as output, Z_i must be inverted to obtain $\hat{X}_i = Z_i^{-1}(Z_i\hat{X}_i)$.

The above filter formulation has been based on n solutions being carried on in parallel, each assuming that x_3 was in proximity to a particular γ_i. The γ_i were chosen to lie at equal intervals between 0 and π. After the n filters have been processing bearing inputs for some period of time it is desirable to reject all but the correct filter and use its output to calculate a state estimate. In addition, x_3 may be between π and 2π rather than between 0 and π; and this ambiguity must be resolved.

Assume β lies between γ_j and γ_{j+1} where $\gamma_{j+1} - \gamma_j = \Delta\gamma$ and $\beta - \gamma_j = \varepsilon$. Then ideally the j^{th} filter will have an output

$$(\hat{x}_3)_j = \beta - \gamma_j = \varepsilon > 0 .$$

The j+1th filter will have an output

$$(\hat{x}_3)_{j+1} = \beta - \gamma_{j+1} = \varepsilon - \Delta\gamma < 0 .$$

The test to locate the correct filter pair, j and j+1, consists of tabulating all cases in which

$$(\hat{x}_3)_j > 0 \text{ and } (\hat{x}_3)_{j+1} < 0$$

and then selecting the pair which minimizes

$$|(\hat{x}_3)_j - (\hat{x}_3)_{j+1} - \Delta\gamma|$$

In general only one or two pairs of adjacent filters will pass the test, $(\hat{x}_3)_j > 0$ and $(\hat{x}_3)_{j+1} < 0$. Linear interpolation between the outputs of the selected filter pair yields the final state estimate:

$$\hat{X} = \frac{-(\hat{x}_3)_{j+1}}{(\hat{x}_3)_j - (\hat{x}_3)_{j+1}} \begin{bmatrix} (\hat{x}_1)_j \\ (\hat{x}_2)_j \\ \gamma_j \end{bmatrix} + \frac{(\hat{x}_3)_j}{(\hat{x}_3)_j - (\hat{x}_3)_{j+1}} \begin{bmatrix} (\hat{x}_1)_{j+1} \\ (\hat{x}_2)_{j+1} \\ \gamma_{j+1} \end{bmatrix}.$$

The ambiguity of π in β exists because the tangent function is periodic with period π. This ambiguity can be resolved by using the fact that no observed bearing should differ from β by more than $\pi/2$. Thus comparison of the estimate of β with a recent bearing or average of recent bearings will immediately show whether or not π should be added to achieve consistency with the observed bearing data.

COMPUTER FLOW CHART

Figure 2 shows a flow chart of the bearing tracker. The left most loop processes each input bearing, updating all n filters. All essential information about the state is generated and stored by this loop but not in a form that can be readily outputted. The right hand sequence is used whenever an output is required. It rejects all but two of the n filters, interpolates between them, resolves the ambiguity of π, and outputs the states.

SIMULATION RESULTS

A limited computer simulation has been conducted to evaluate the performance of the bearing tracker. A minicomputer was used to generate a straight line target track, calculate true bearings from a sensor to the target as a function of time, and add Gaussian noise to these bearings. The bearing tracker algorithm, programmed in the same computer, was used to process these noisy bearings to obtain target track parameters. At the end of the target track a comparison was made between the state estimated by the bearing tracker and the true state.

The simulation was limited to a single class of target tracks shown in Figure 3. Tracking began with the target 15000 feet from CPA and continued until the target was 5000 feet past CPA. Closest approach was 8000 feet. Target speed was 16 feet per second, approximately 10 knots. The bearing at CPA, β, was allowed to vary over a limited range.

The Gaussian noise added to the bearing measurements was given a variance proportional to the square of the range to the target. It was assumed that the noisy bearing measurements had been averaged for T seconds before being processed by the bearing tracker. The noise variance for each measurement was determined by the formula:

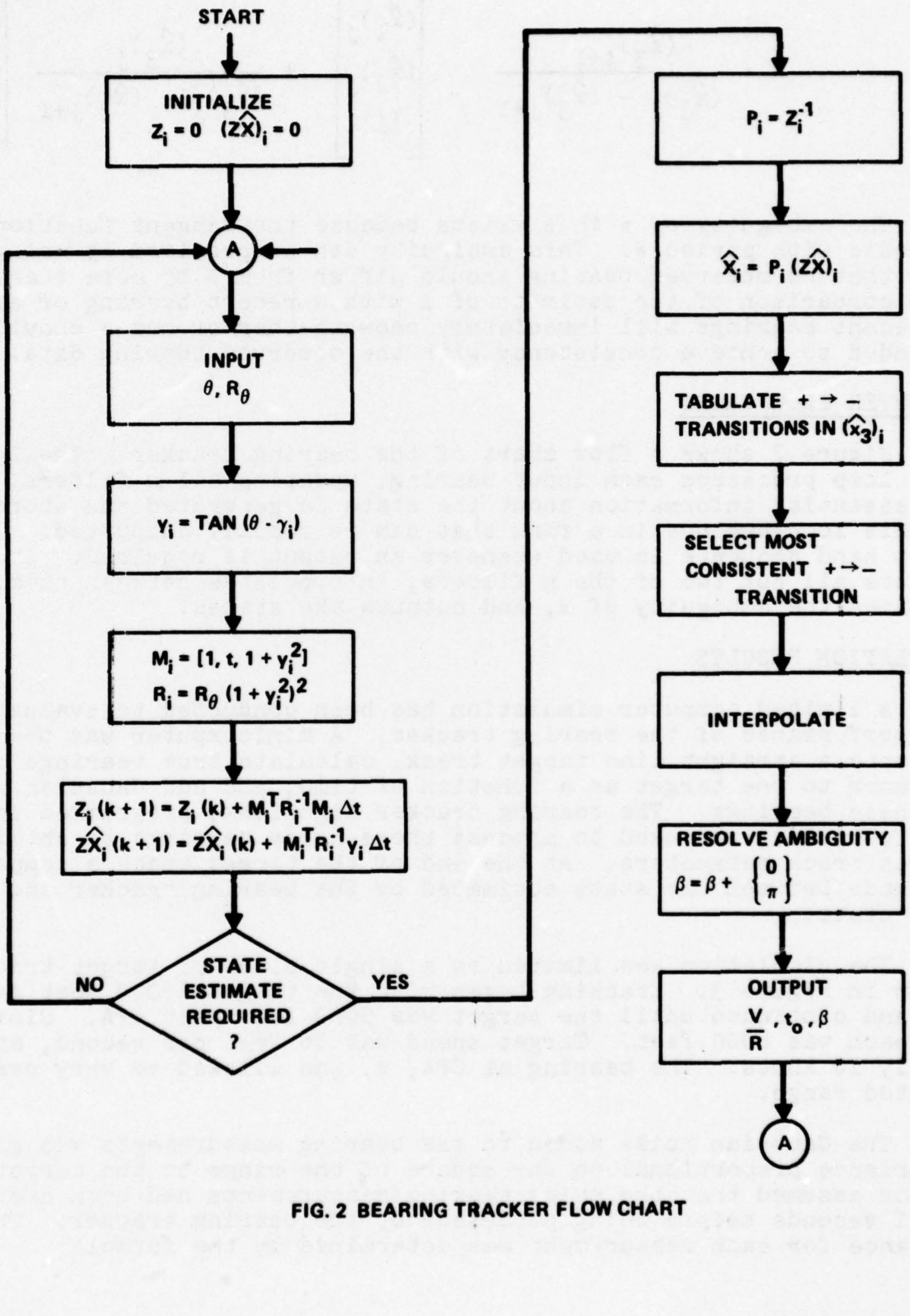

FIG. 2 BEARING TRACKER FLOW CHART

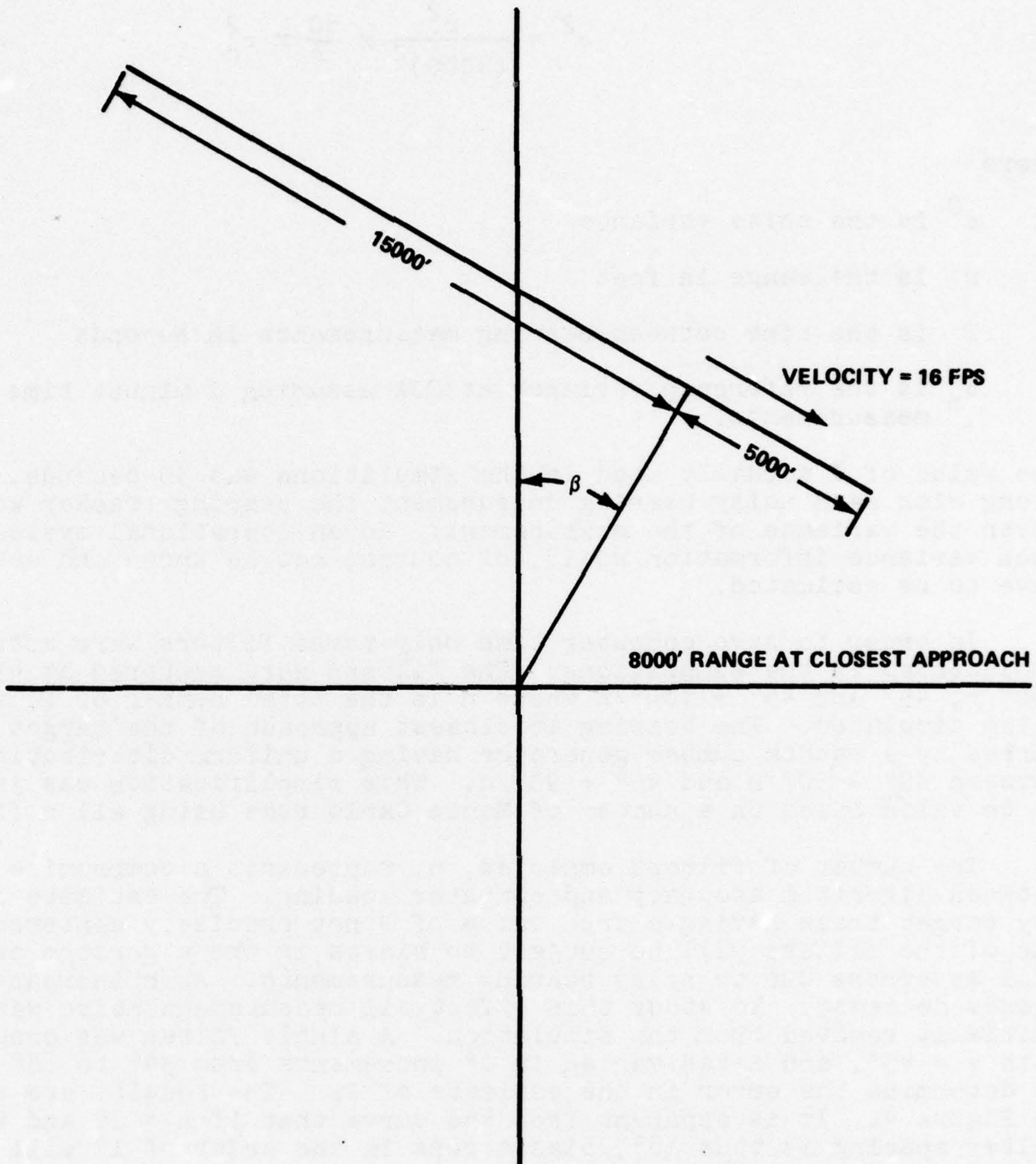

FIG. 3 TARGET TRACK GEOMETRY FOR SIMULATIONS

$$\sigma^2 = \frac{r^2}{(8000)^2} \times \frac{60}{T} \times \sigma_o^2$$

where

σ^2 is the noise variance

r is the range in feet

T is the time between bearing measurements in seconds

σ_o^2 is the reference variance at CPA assuming 1 minute time between measurements.

The value of T actually used in the simulations was 50 seconds. Along with each noisy bearing measurement the bearing tracker was given the variance of the measurement. In an operational system such variance information would, of course, not be known and would have to be estimated.

In order to save computer time only three filters were actually implemented in the simulations. The filters were centered at 45°-180°/n, 45° and 45° + 180°/n where n is the total number of filters being simulated. The bearing at closest approach of the target was varied by a random number generator having a uniform distribution between 45° - 90°/n and 45° + 90°/n. This simplification was judged to be valid based on a number of Monte Carlo runs using all n filters.

The number of filters employed, n, represents a compromise between algorithm accuracy and computer loading. The estimate of any target track having a true value of β not precisely centered on one of the filters will be subject to biases in the algorithm as well as errors due to noisy bearing measurements. As n increases these biases decrease. To study this effect all measurement noise was initially removed from the simulation. A single filter was programmed with γ = 45°, and β was varied in 1° increments from 34° to 68° to determine the error in the estimate of β. The results are shown in Figure 4. It is apparent from the curve that if n = 10 and the filter spacing is thus 18°, bias errors in the order of 1° will result. To verify the relationship between error in the state estimate and n, a Monte Carlo analysis was run with a very small value of bearing measurement noise, .1°. The number of filters was varied between 5 and 100. The observed errors in the state estimate were normalized to the errors which should be achieved by an ideal extended Kalman filter. The performance of the ideal filter was evaluated with the expression[1]

[1]Jazwinski, A. H., Stochastic Process and Filtering Theory, Academic Press, 1970.

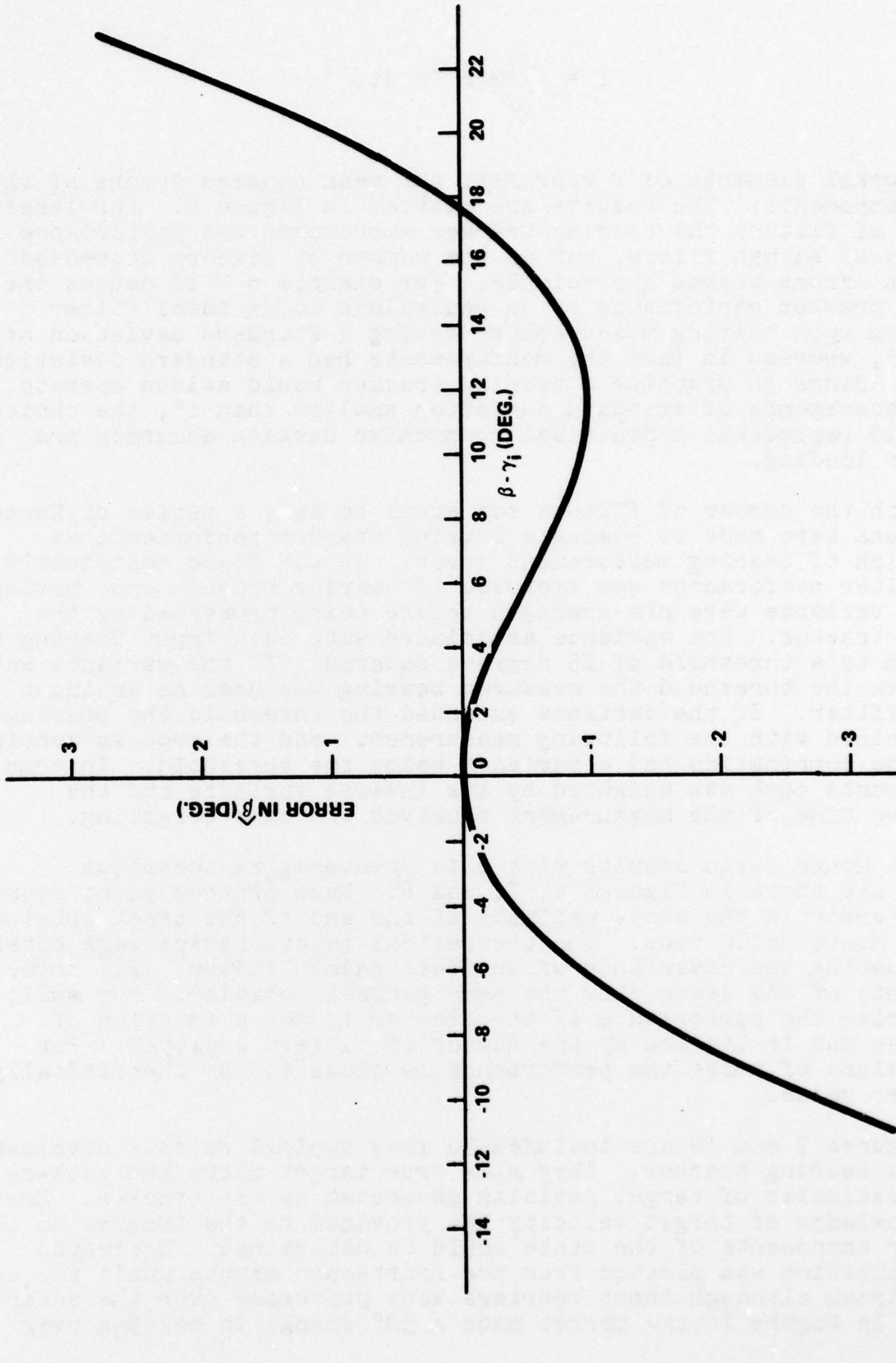

FIG. 4 ERROR IN $\hat{\beta}$ AS A FUNCTION OF $\beta - \gamma_i$

$$P = \left[\int_0^T M^T R^{-1} M \, dt\right]^{-1}$$

The diagonal elements of P represent the mean squared errors of the state components. The results are plotted in Figure 5. For large numbers of filters the bearing tracker approaches the performance of an ideal Kalman filter, but as the number of filters decreases the bias errors become appreciable. For example n = 10 causes the bearing tracker performance to be equivalent to an ideal filter operating upon bearing measurements having a standard deviation of about 1°, whereas in fact the measurements had a standard deviation of .1°. Since in practice a bearing tracker would seldom operate upon measurements of standard deviation smaller than 1°, the choice of n = 10 represents a practical compromise between accuracy and computer loading.

With the number of filters set equal to ten, a series of Monte Carlo runs were made to evaluate bearing tracker performance as a function of bearing measurement error. It was found empirically that filter performance was improved if bearing measurements having a large variance were pre-averaged before being processed by the bearing tracker. The variance associated with each input bearing was compared to a threshold of 25 degrees squared. If the variance was less than the threshold the measured bearing was used as an input to the filter. If the variance exceeded the threshold the bearing was combined with the following measurement and the process continued until the combination had a variance below the threshold. In combining measurements each was weighted by its inverse variance and the effective time of the measurement received the same weighting.

The Monte Carlo results with this preaveraging technique applied are shown in Figures 6, 7, and 8. Each plotted point represents the RMS error in the state estimate at the end of the track obtained from 50 Monte Carlo runs. The theoretical relationships were obtained by evaluating the covariance of an ideal Kalman filter. All three components of the state show the same general behavior. For small input noise the performance of the tracker is not a function of the noise but is limited by the number of filters employed. For large values of noise the performance is close to the theoretically predicted value.

Figures 9 and 10 are included to show typical results obtainable with the bearing tracker. They show true target paths and once-a-minute estimates of target position generated by the tracker. Error free knowledge of target velocity was provided to the tracker so that all four components of the state could be determined. Estimated target position was plotted from the fourteenth minute until the end of the track although input bearings were processed over the entire track. In Figure 10 the target made a 30° change in heading over

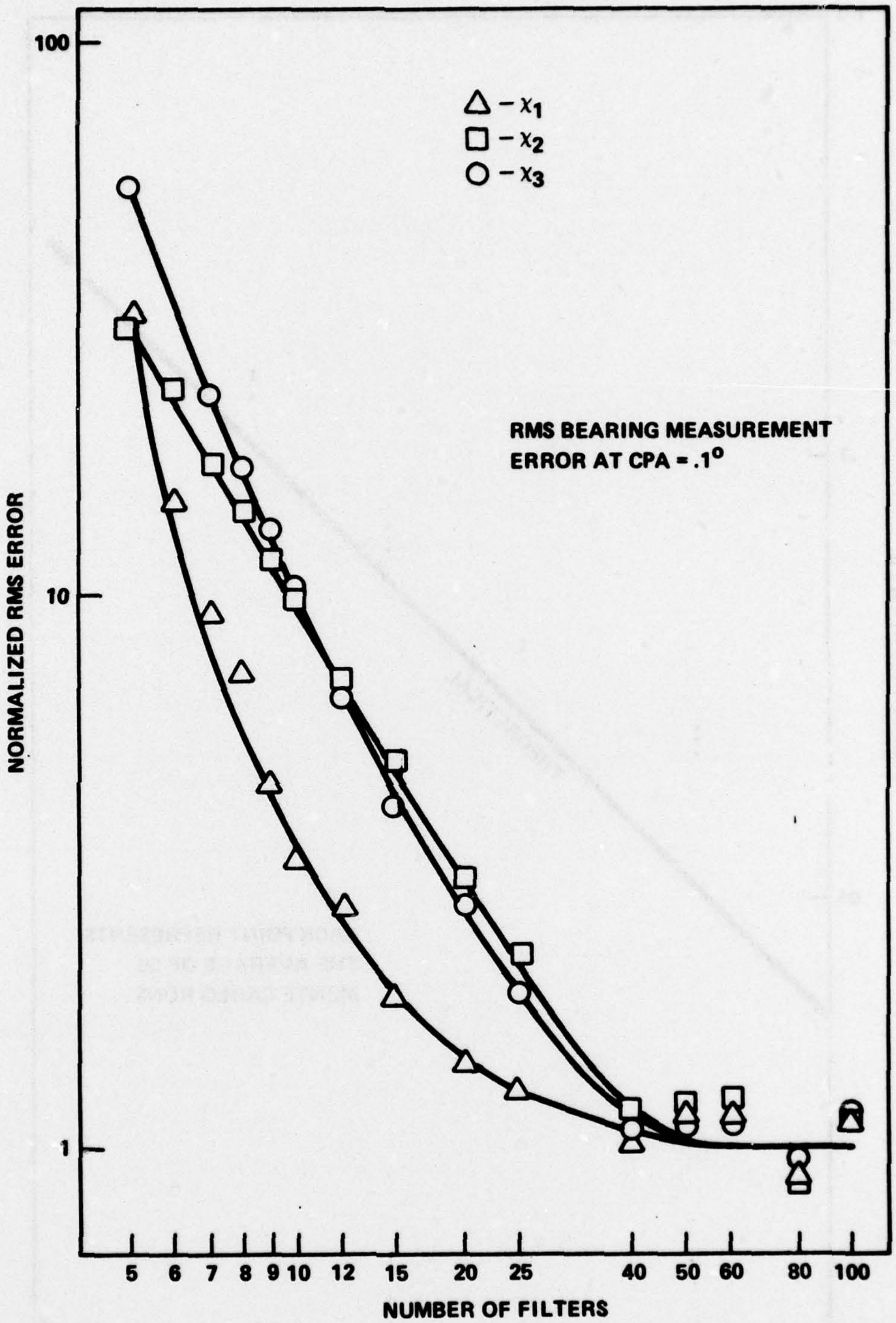

FIG. 5 NORMALIZED RMS ERRORS AS A FUNCTION OF NUMBER OF FILTERS

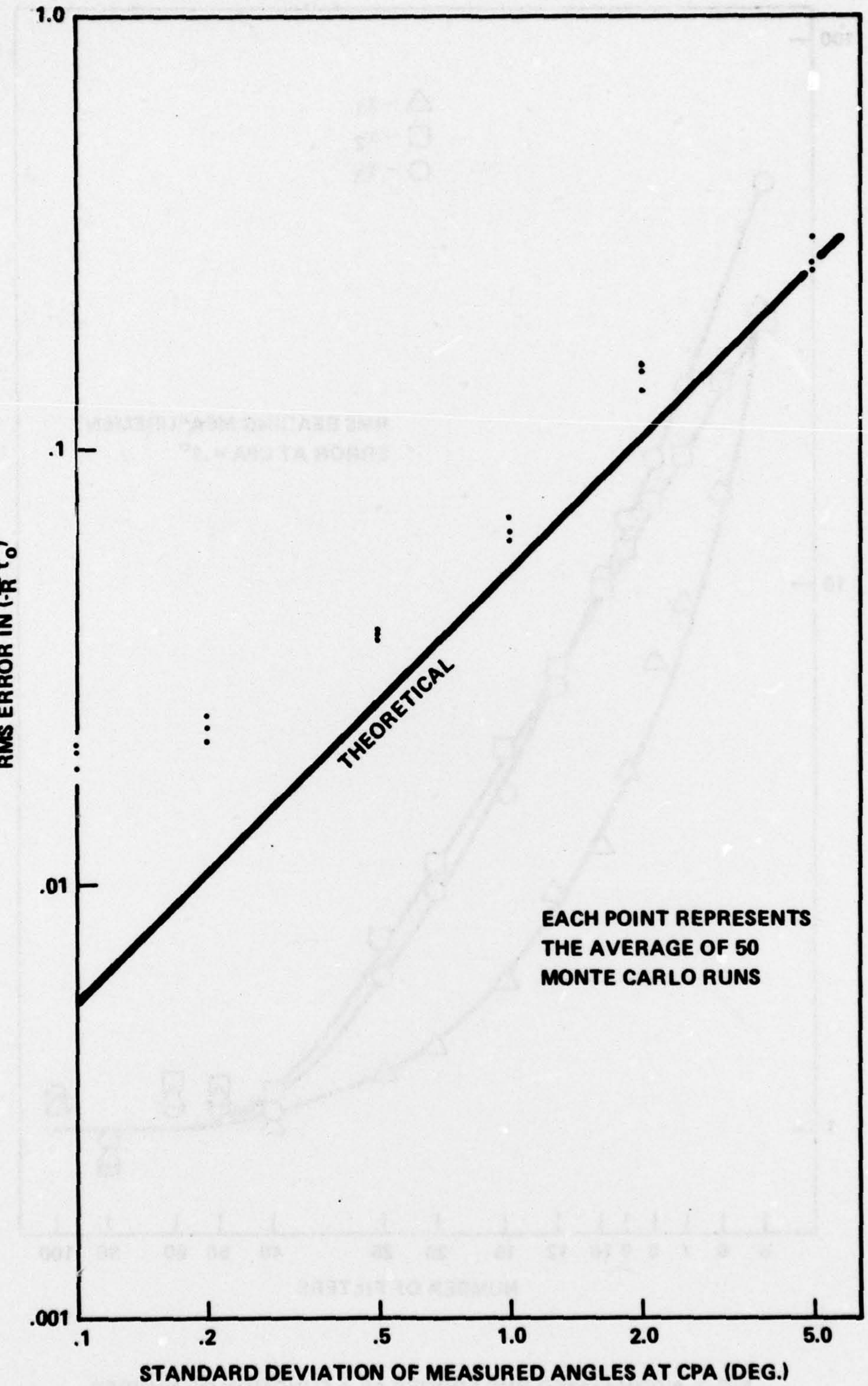

FIG. 6 ERROR IN χ_1 vs. BEARING ERROR AT CPA.

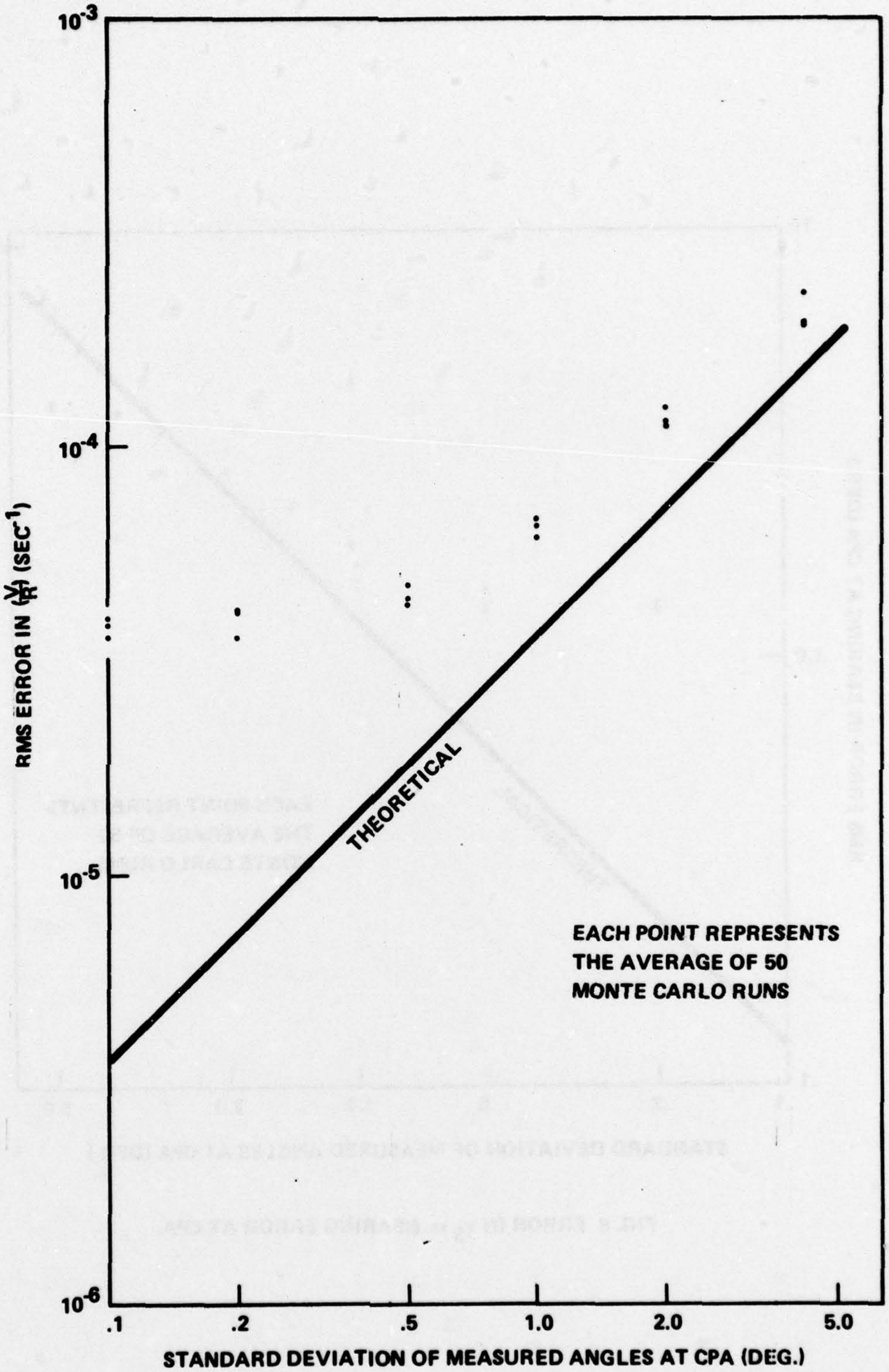

FIG. 7 ERROR IN χ_2 vs. BEARING ERROR AT CPA.

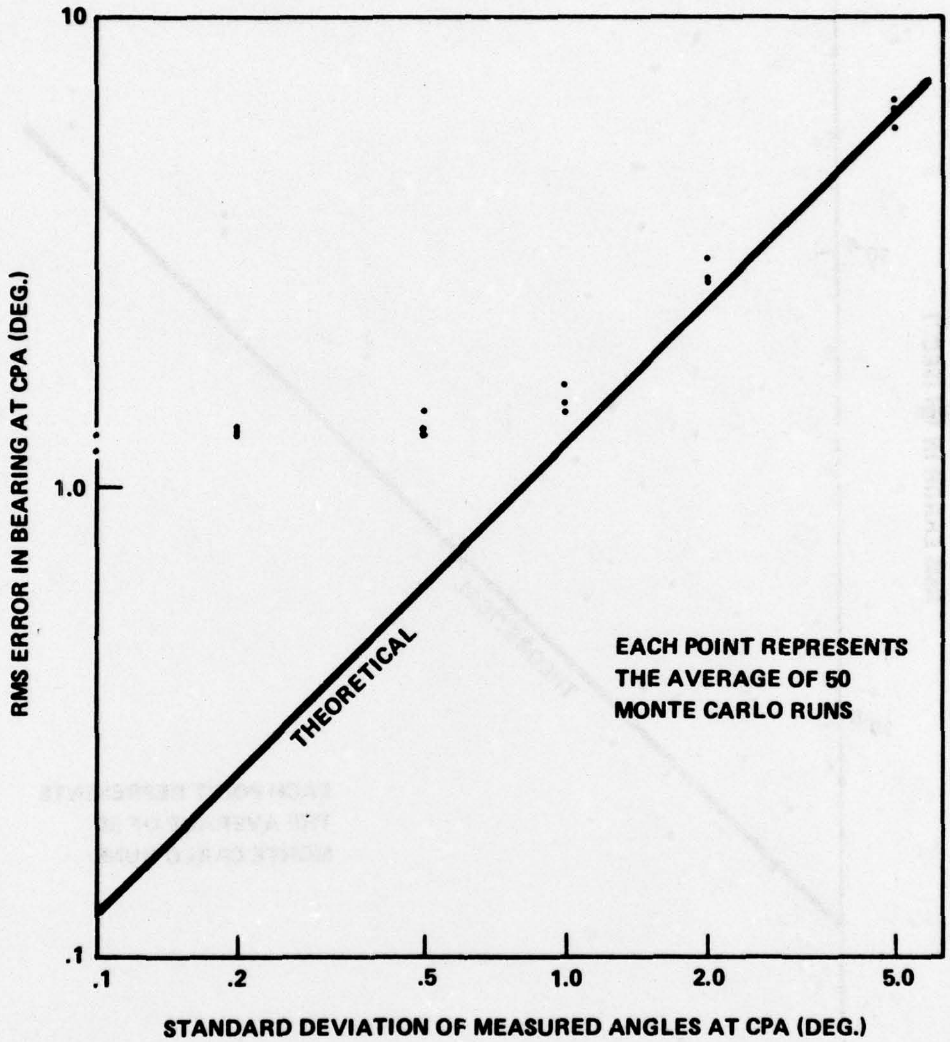

FIG. 8 ERROR IN χ_3 vs. BEARING ERROR AT CPA.

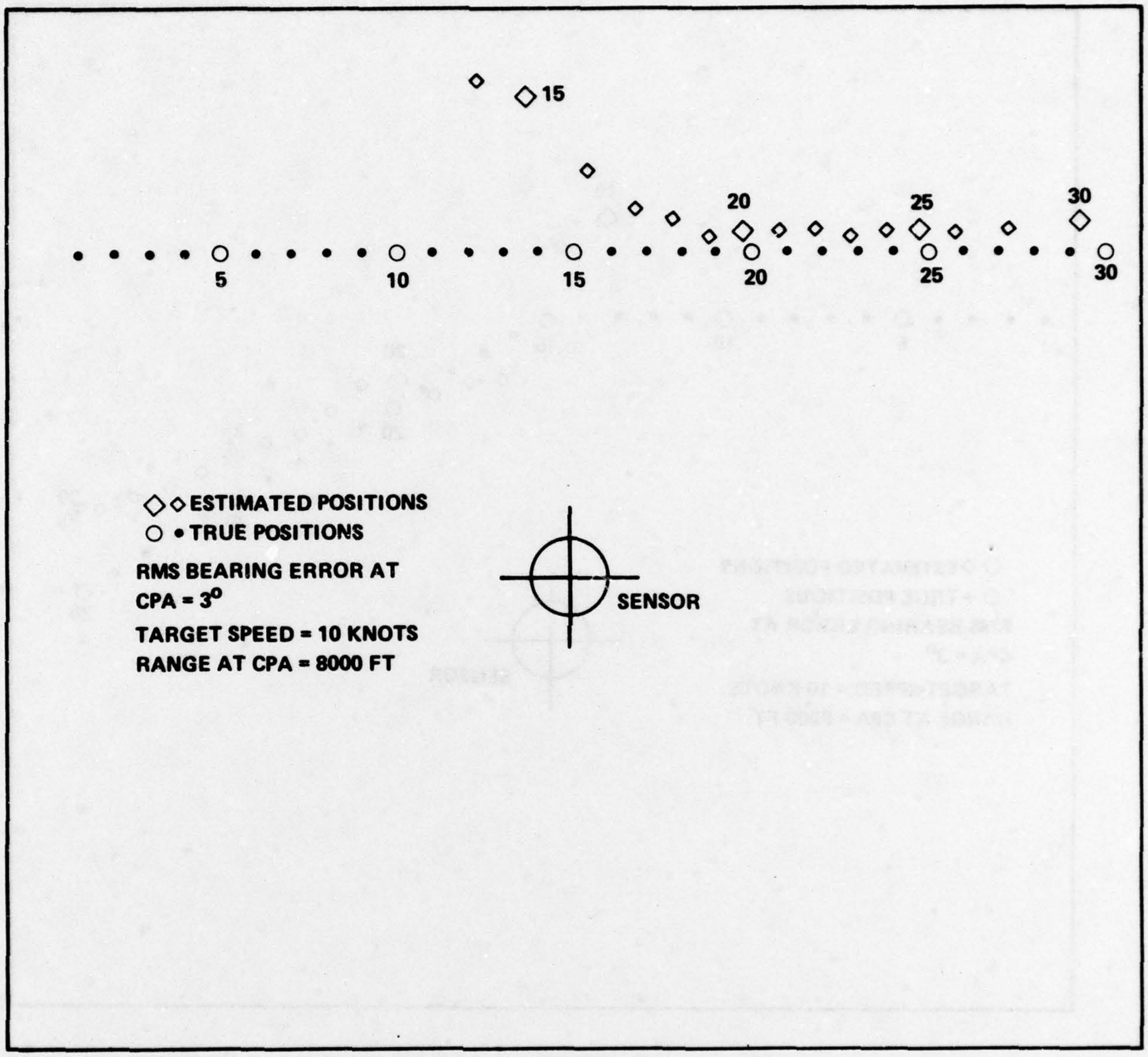

FIG. 9 TYPICAL BEARING TRACKER PERFORMANCE

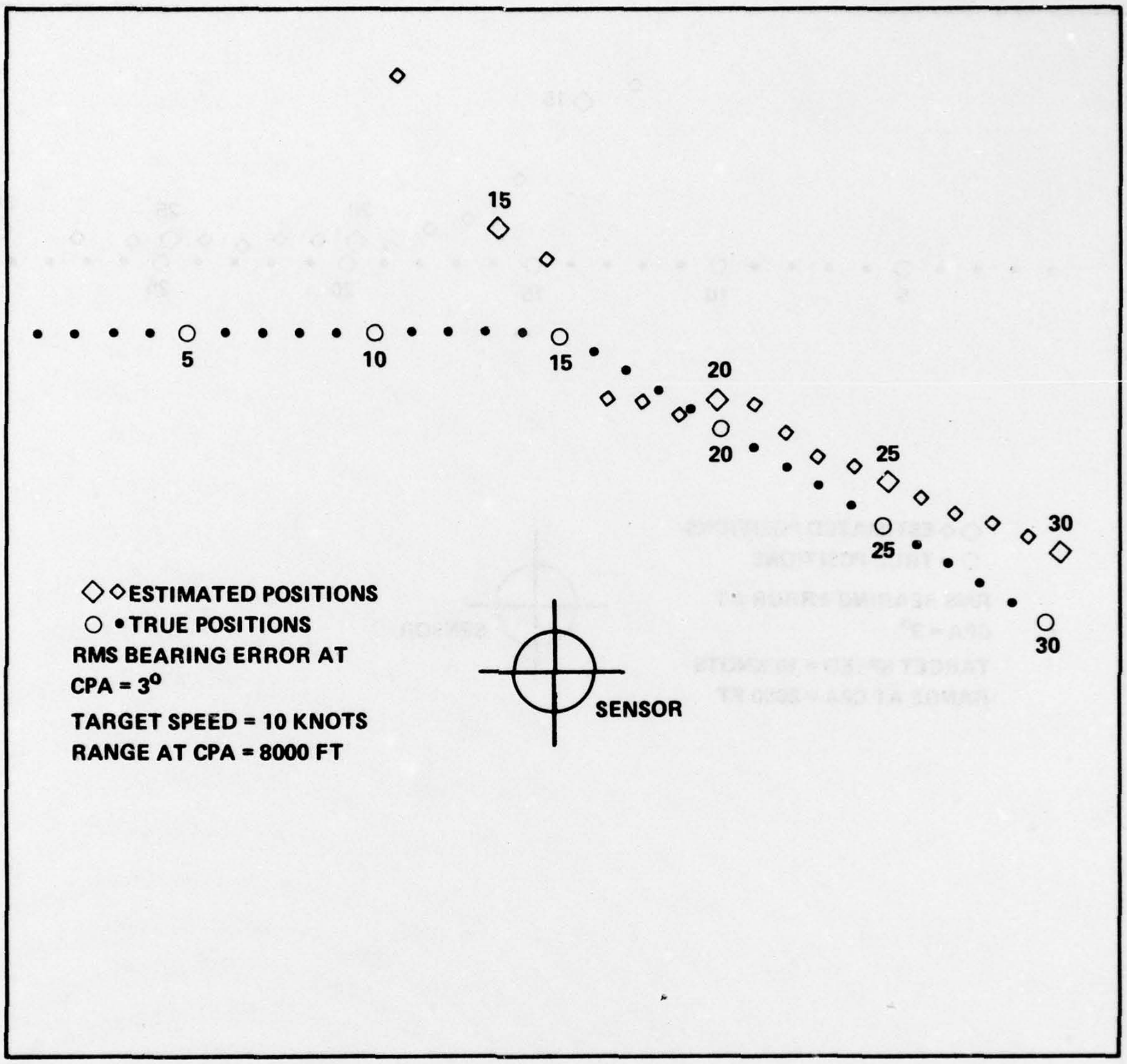

FIG. 10 TYPICAL BEARING TRACKER PERFORMANCE WITH MANEUVERING TARGET

a 2 minute period. After a sufficient volume of input data about the new course had been processed the tracker correctly evaluated the new value of β and slowly de-emphasized the data collected prior to the maneuver. The overshoot exhibited in this case is typical of the tracker response to mild maneuvers.

SUMMARY OF RESULTS

Limited computer simulations show generally good agreement between the performance of the bearing tracker and the theoretical performance of a maximum likelihood estimator. At high signal to noise ratios the bearing tracker becomes sub-optimum, but the overall result is a system which will function very well with input bearing errors up to 5° at CPA based on one minute integration of the noise.

The major advantages of the algorithm are that it requires no initialization and never becomes irrevocably committed to a particular solution.

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PENALTY FOR PRIVATE USE, $300

POSTAGE AND FEES PAID
DEPARTMENT OF THE NAVY
DOD 316

COMMANDER
NAVAL SURFACE WEAPONS CENTER
WHITE OAK, SILVER SPRING, MARYLAND 20910

ATTENTION: CODE WU-22