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MODELING METHODOLOGY FOR MLS RANGE NAVIGATION
SYSTEM ERRORS USING FLIGHT TEST DATA

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PREFACE

This effort was performed under Contract No.
NAS2-10670, Mod 2 from the NASA/Ames Research Center.
Dr. John Bull of NASA-Ames was the technical monitor
for this project.

The project manager at AMA Inc. was Dr. Anil
V. Phatak and project engineer was Mehebub S. Karmali.

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INTRODUCTION

The ability of a helicopter to fly a prescribed flight path and speed profile is intimately dependent upon the accuracy of the position and velocity estimates provided by the navigation system. Typically, a navigation system must process raw position data (aircraft range, azimuth and elevation signals) provided by a ground-based landing guidance system (LGS) using an on-board digital processor, to obtain estimates of the aircraft position and range rate. These estimates are then used by the pilot or an automatic guidance and control system to fly the helicopter along a commanded position and velocity profile.

In order to evaluate the sensitivity of the helicopter performance (in terms of errors in following desired position and velocity profile) to the navigation system errors, it is necessary to analyze and model the raw navigation signals from the ground-based LGS as well as their on-board processing to provide the aircraft position and rate estimates. A routinely used mathematical model for the overall navigation system is as shown in Figure 1. The model consists of a ground-based element describing the generation of the raw position signal (range, azimuth or elevation) y_m by the LGS and an airborne element representing the on-board processing of the raw position signal y_m to provide the estimate $\hat{y}$. The position error or noise $(y_m - y)$ in the raw measurement signal is modeled as the sum of a zero mean correlated random process n (with correlation time constant τ_n and standard deviation σ_n) and a constant bias error b. The on-board processor typically consists of a sampler and quantizer followed by a second-order low pass filter (usually an α-β filter configuration) whose outputs provide position and rate estimates. The configuration and parameters of the on-board navigation system depend upon the ground-based signal accuracy, and must be based upon apriori knowledge of the noise characteristics.

Mathematical models as shown in Figure 1 are frequently used in off-line or piloted simulation investigations of helicopter navigation, guidance and control system performance. The usefulness of the findings from such studies is clearly related to the veracity of the mathematical models used to represent individual subsystems.

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Ground–Based
Element (LGS)

Airborne Element

$\eta \approx N(0,1)$

$$\dfrac{K_n}{\tau_n s + 1}$$

On–Board Processor

| Sampler & Quantizer | 2nd Order Filter |

y_m

y

$\hat{y}$

n

b
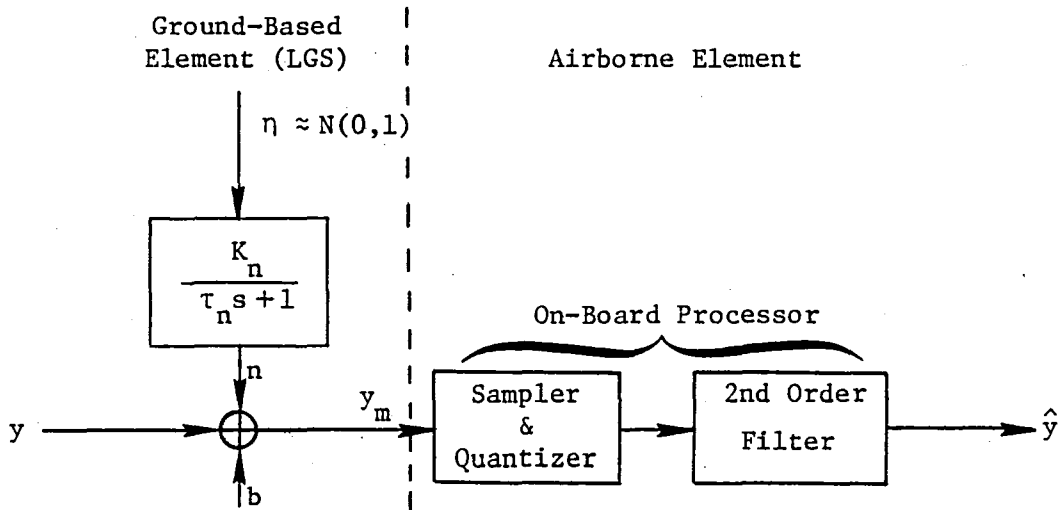
y_m : raw position signal (range, azimuth or elevation)

y : true aircraft position

n : colored measurement noise

b : measurement bias

η : Gaussian noise; zero mean and unity std. dev.

τ_n : noise correlation time constant

K_n : noise filter gain

Figure 1. Navigation System Model

OBJECTIVE

The objective of this study was to develop a possible mathematical methodology for describing the navigation signal error or noise characteristics (range only) of the microwave landing system (MLS) using flight test data during constant speed/glideslope helicopter approaches. The MLS range navigation system error was analyzed to determine the feasibility of identifying a Gauss-Markov stochastic model structure.

MLS NAVIGATION ERROR ANALYSIS

This section presents the results of analyzing the MLS range naviga-
tion system estimate $\hat{r}$ from a modeling viewpoint. Data from NASA/FAA
flight tests conducted at NASA's Crows Landing test facility were used.
The characteristics of the combination of the on-board processor and
the ground-based LGS noise were analyzed from measurements of the
navigation system error ($r_{NSE} = r - \hat{r}$) time history. Note that both
the true range r and the estimate range $\hat{r}$ must be available to extract
the navigation system error. A time history of the true range r was
available at NASA's Crows Landing facility when these flight tests
were conducted from the TTR and MTR radars. However, even the radar
position measurements were not without noise as is shown later and
cannot be used without some filtering/smoothing. Furthermore, the
position provided by the MTR radar differed from that obtained from
the TTR radar. The difference was usually less than about $\pm$ 5 ft in
each coordinate (x, y and z) but could be as high as $\pm$ 20 ft. As a
result, the approach taken in this study was to assume the smoothed
or low frequency component of radar range to be the true range (r)
time history. Thus:

$$r_{MN} = \hat{r} - r_M^o$$

where $\hat{r}$ = MLS range

r_M^o = low frequency component of MLS range

r_{MN} = random component of MLS range.

As a check, a similar procedure is applied to TTR radar data to give

$$r_{RN} = r_R - r_R^o$$

where r_R = radar range

r_R^o = low frequency component of radar range

r_{RN} = random component of radar range.

The low frequency components r_M^o and r_R^o should ideally be obtained by filtering/smoothing the actual MLS and radar measurements $\hat{r}$ and r_R, respectively. However, the application of these algorithms for reference trajectory computation was considered beyond the scope of this preliminary effort. Instead, the following sequence of steps (essentially a linearization of the problem) was used to compute the smoothed and random components.

1. Plot MLS range $\hat{r}$ versus time and select the time segment corresponding to a constant speed/glideslope approach. Fit the MLS range versus time plot with a straight line $\hat{r}^* = -\alpha t + \hat{r}_o$, where slope $-\alpha$ corresponds to the average constant range rate of the helicopter.

2. Compute and plot the MLS range residual (MRR)

   $$MRR = \hat{r} - \hat{r}^*$$

   versus time.

3. Filter MRR with a low pass path following error filter (PFEF) as described in the Appendix to extract the "linearized" MLS path following error (MPFE).

4. Subtract MPFE from MRR to compute the MLS path following range residual (MPFRR)

   $$MPFRR = MRR - MPFE$$

5. Filter MPFRR with a high pass control motion noise filter (CMNF) as described in the Appendix whose output is the MLS control motion noise (MCMN), the random error component of the MLS range.

   $$r_{MN} \equiv MCMN$$

Steps (1-5) were also applied to radar (TTR) range data. The variable names are obtained by replacing 'M' with 'R'; thus:

MLS	Radar
$\hat{r}$	r_R
$\hat{r}^*$	r_R^*
MRR	RRR
MPFE	RPFE
MPFRR	RPFRR
MCMN	RCMN
r_{MN}	r_{RN}
r_M^o	r_R^o

Steps (1-5) are applied to one sample of MLS·range data corresponding to a 3° G/S constant speed approach. Figures (2-7) show the plots of $\hat{r}$, $\hat{r}^*$, MRR, MPFE, MPFRR, and MCMN ($\equiv r_{MN}$), respectively. Similarly, Figures (8-11) show the results for radar range data (TTR radar) for the same approach profile where the figure numbers correspond to variables RRR, RPFE, RPFRR, and RCMN ($\equiv r_{RN}$), respectively. In both cases, the PFEF and CMNF filters (described in Appendix) have $\omega_0 = 0.6$ rad/s and $\omega_1 = 0.6$ rad/s, respectively. These values were chosen by trial and error and reflect a tradeoff in separating low frequency actual aircraft motion from high frequency navigation noise.

Figure 11 shows that RCMN ($\equiv r_{RN}$) may be neglected. Thus, the low frequency component of radar range (r_R^o) is assumed to be the true range (r). Comparison of MPFE and RPFE (Fig. 12) indicates that the MLS low frequency error component is essentially zero, since:

$$MPFE \equiv RPFE .$$

This indicates that the MLS and radar measurements are essentially equal for low frequencies, or that

$$r_M^o \equiv r_R^o \equiv r$$

Thus

$$MCMN \equiv r_{MN} \equiv r_{NSE}$$

is the MLS navigation system error. The remainder of the results deal with analyzing the statistical properties of r_{NSE} as shown in Fig. 7.
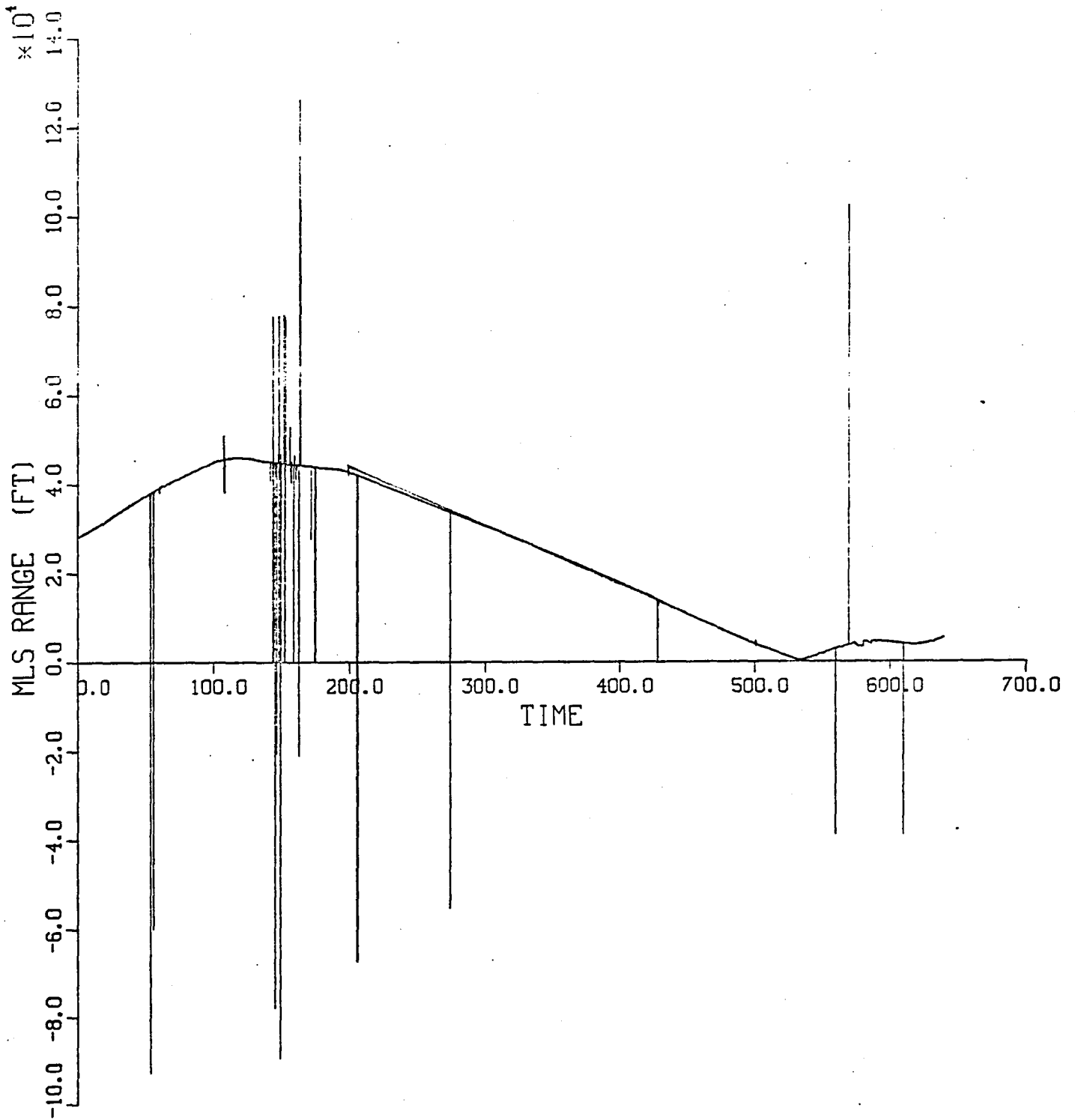
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MLS RANGE (FṪ)

Figure 2.   Raw MLS Range Data (3° G/S Approach): $\hat{r}$
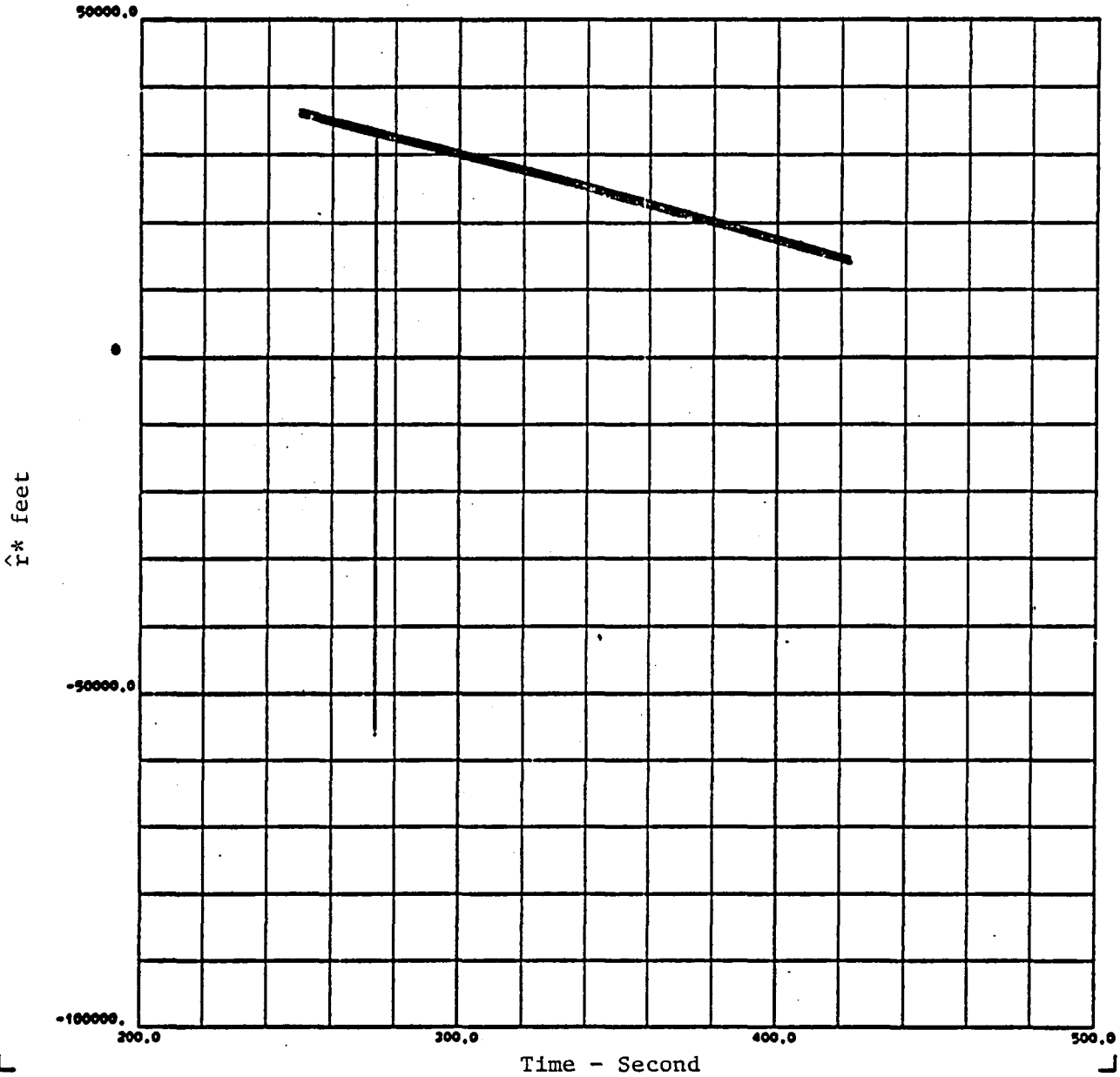
U1418A FILE 1 3-DEG APPROACH

Figure 3. Straight Line Fit $\hat{r}* = -\alpha t + \hat{r}_o$; $\alpha = 121.0$ ft/s, $\hat{r}_o = 80172.$ ft
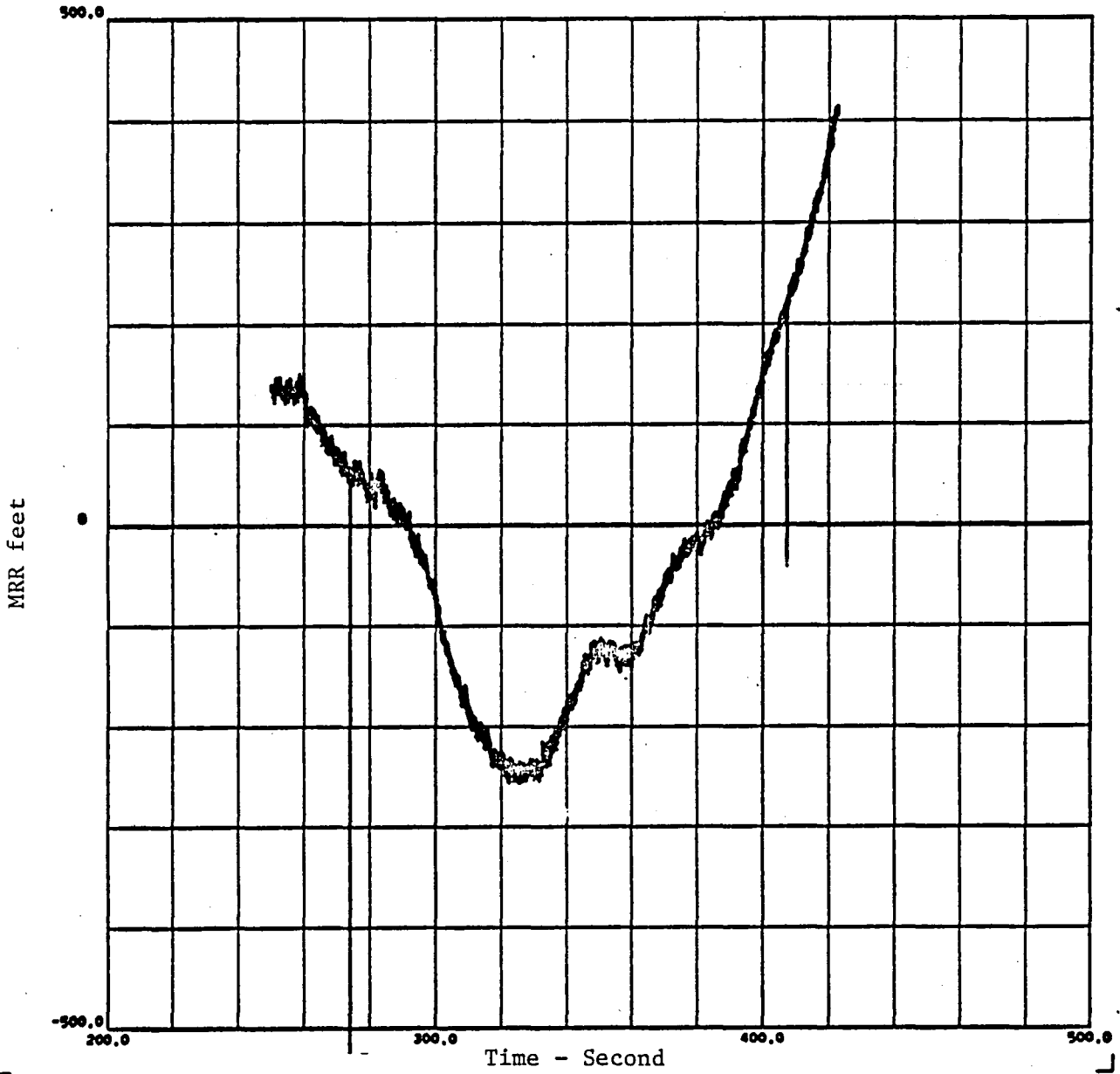
8

Figure 4. MLS Range Residual: MRR
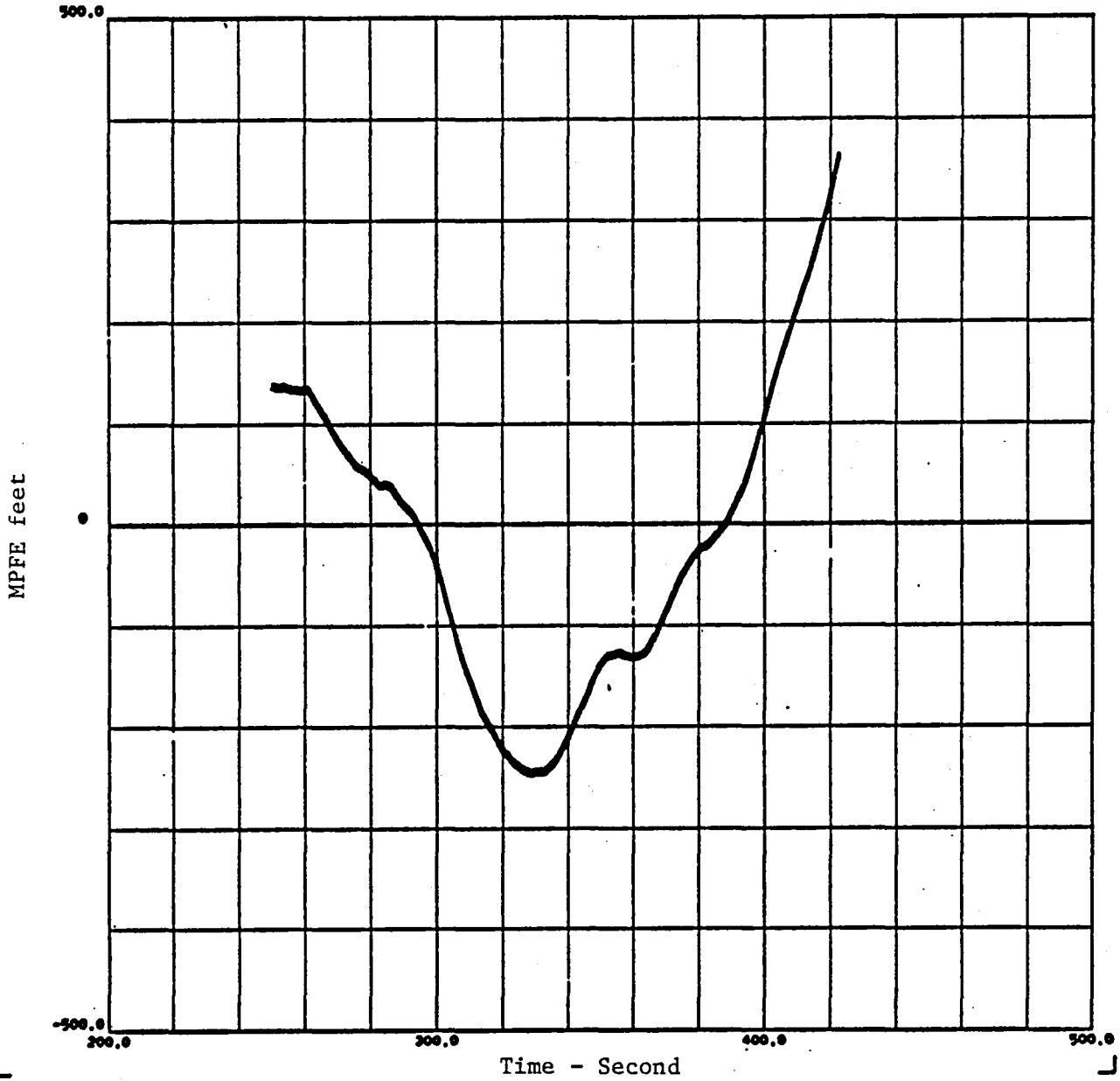
Figure 5.   MLS Path Following Error: MPFE

Figure 6. MLS Path Following Range Residual: MPFRR
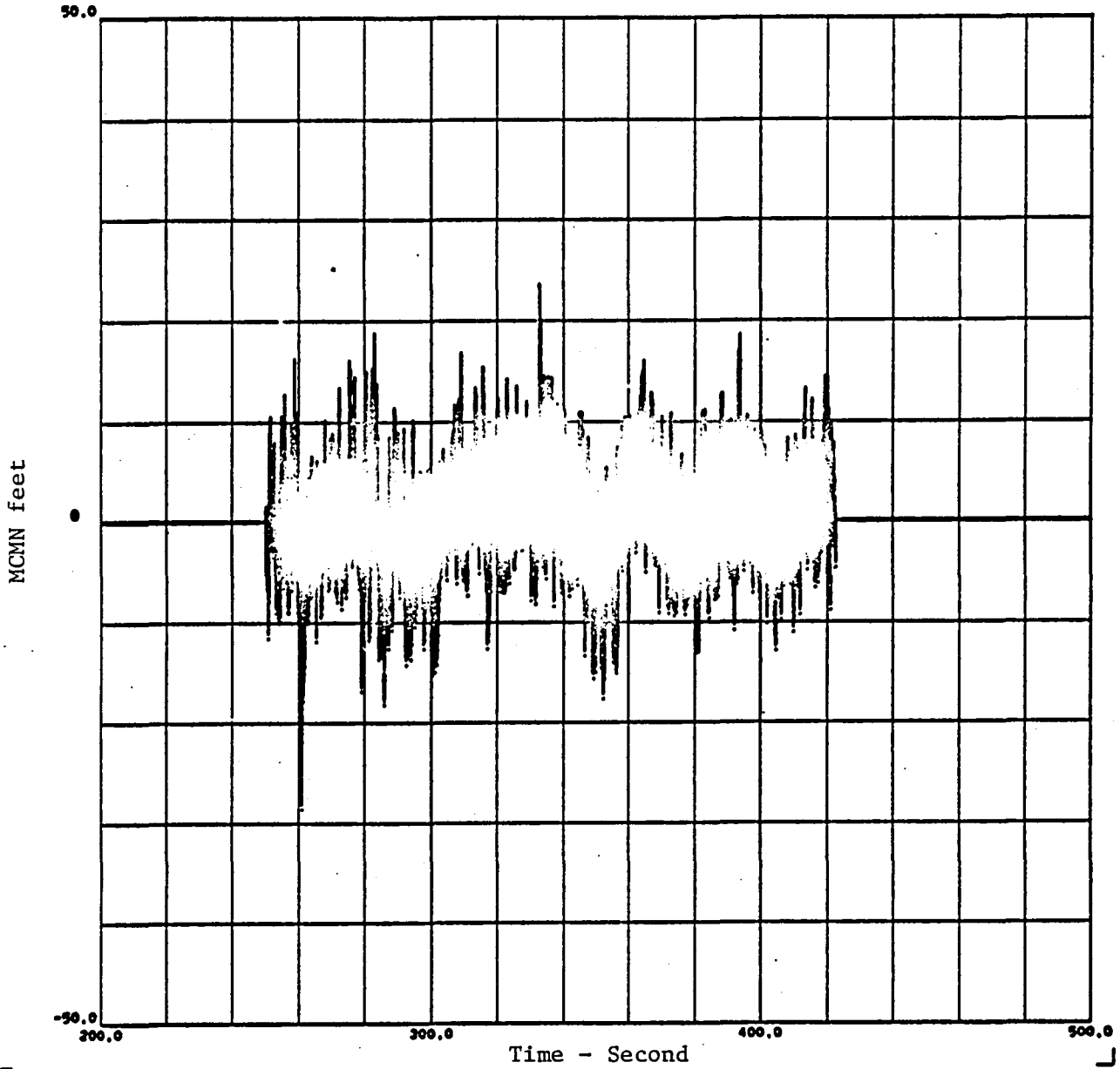
Figure 7. MLS Control Motion Noise: MCMN ($\equiv r_{MN} \equiv r_{NSE}$)

U1418A FILE 1 3-DEG APPROACH
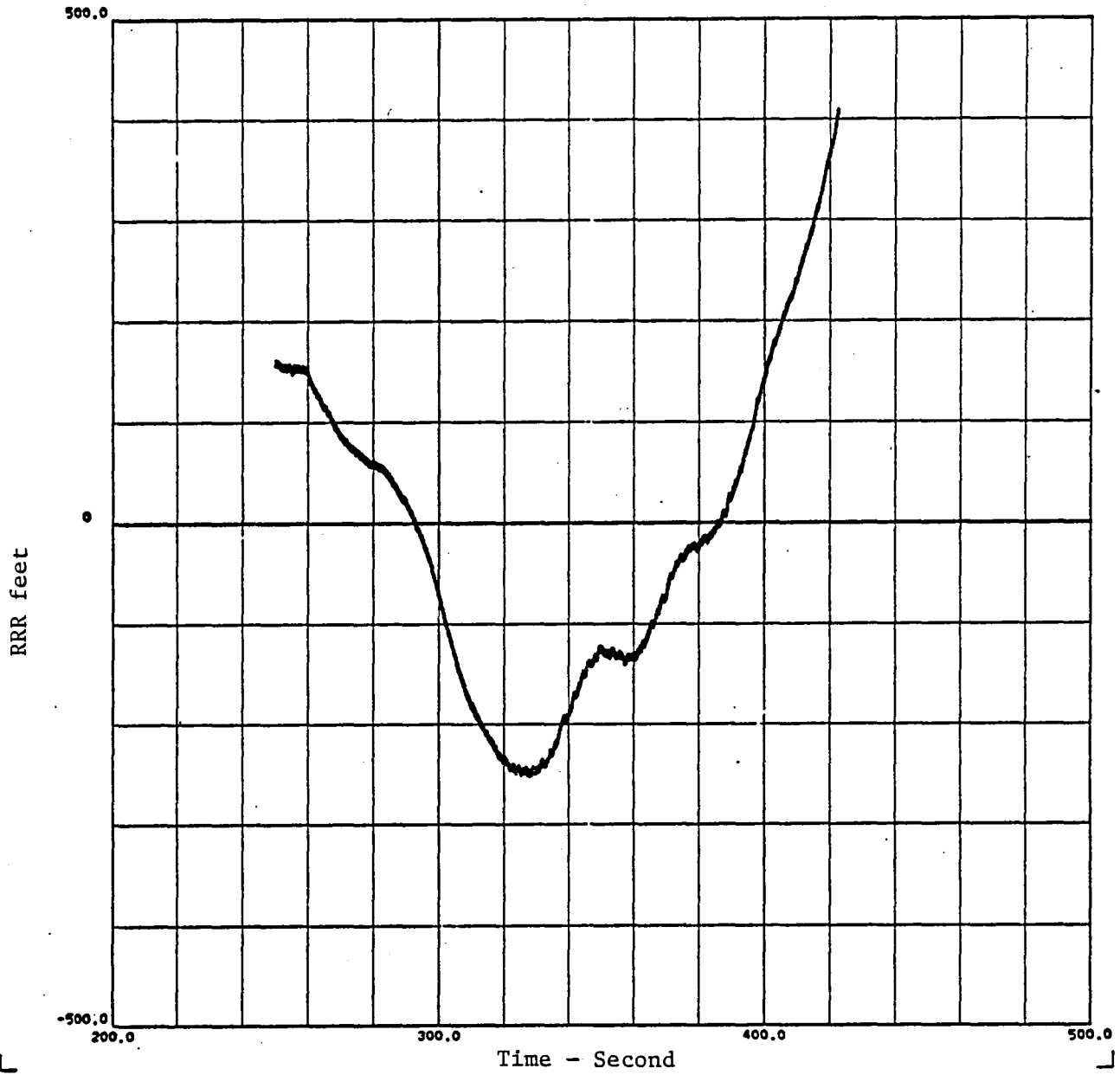
Figure 8.   Radar Range Residual: RRR
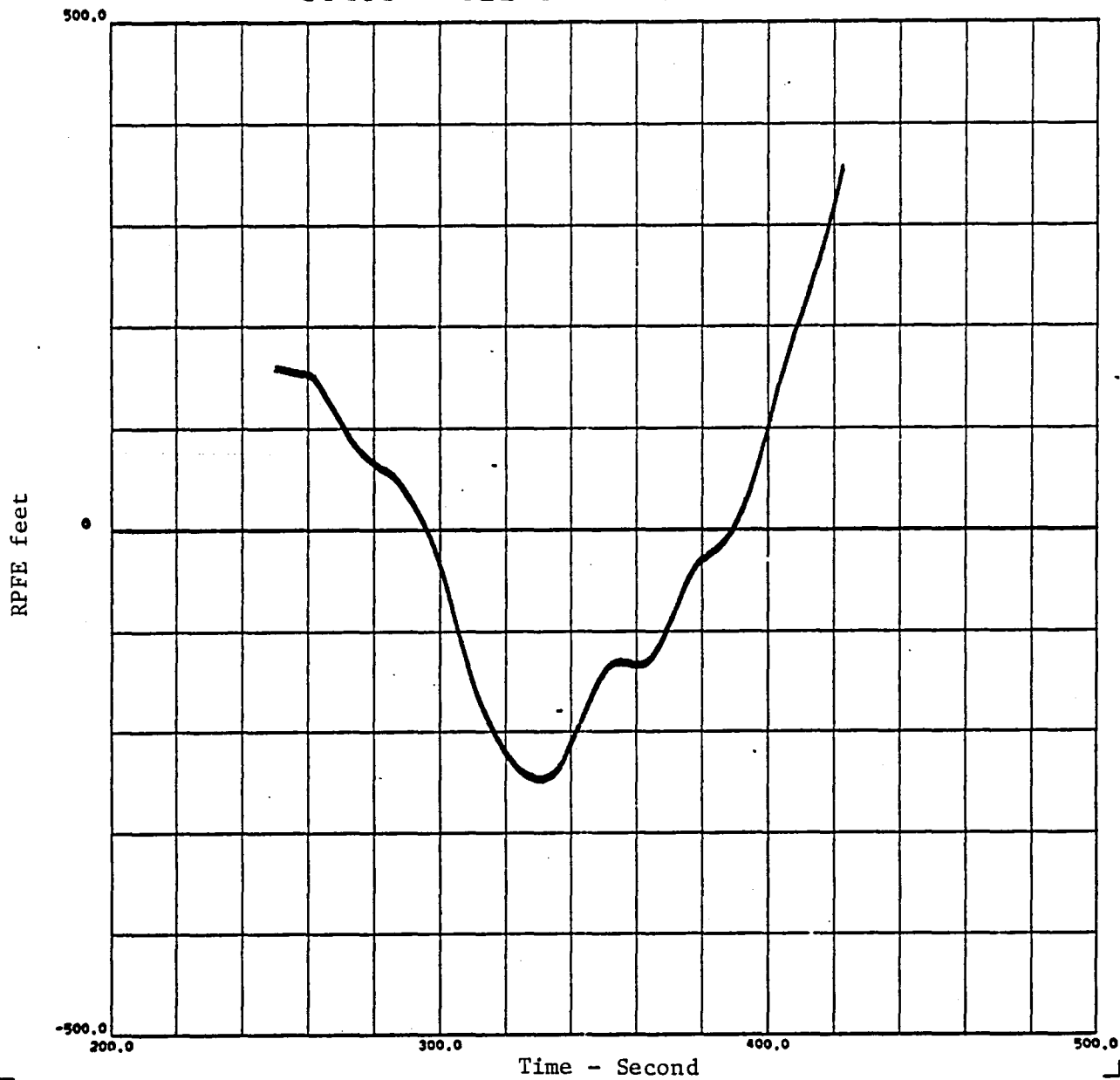
Figure 9.   Radar Path Following Error: RPFE

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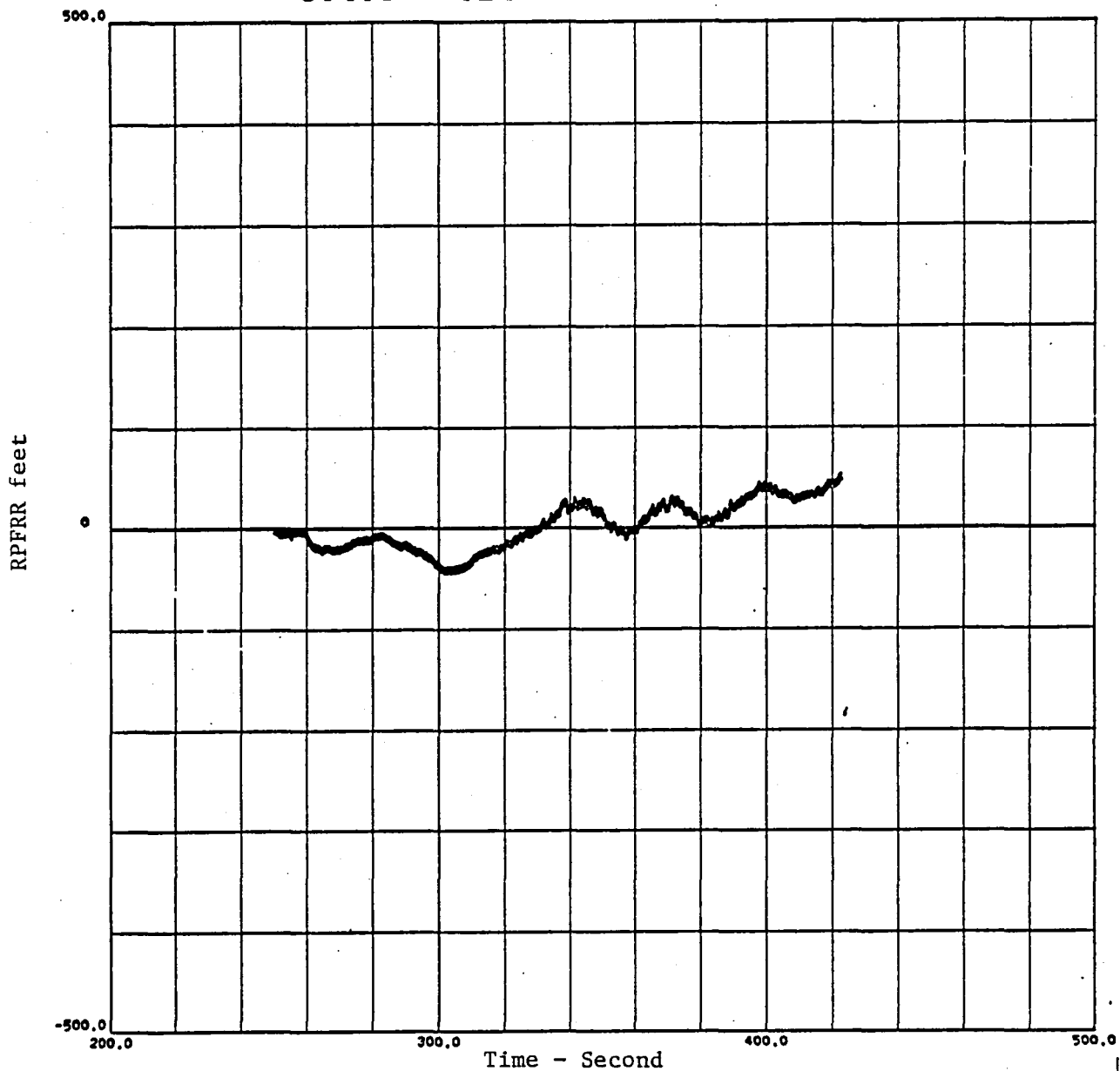
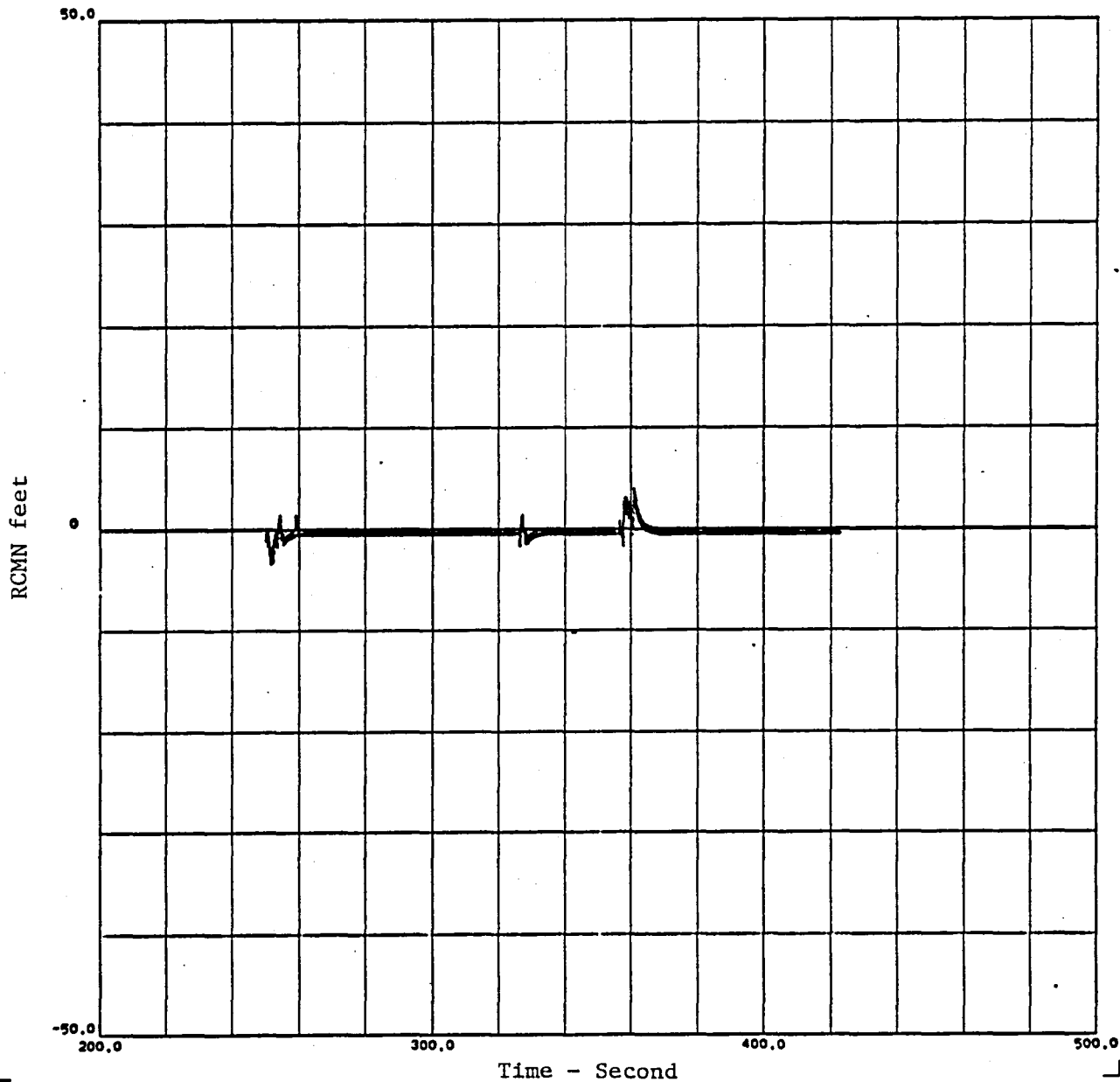Figure 10.   Radar Path Following Range Residual: RPFRR

Figure 11.   Radar Control Motion Noise: RCMN ($\equiv r_{RN}$)
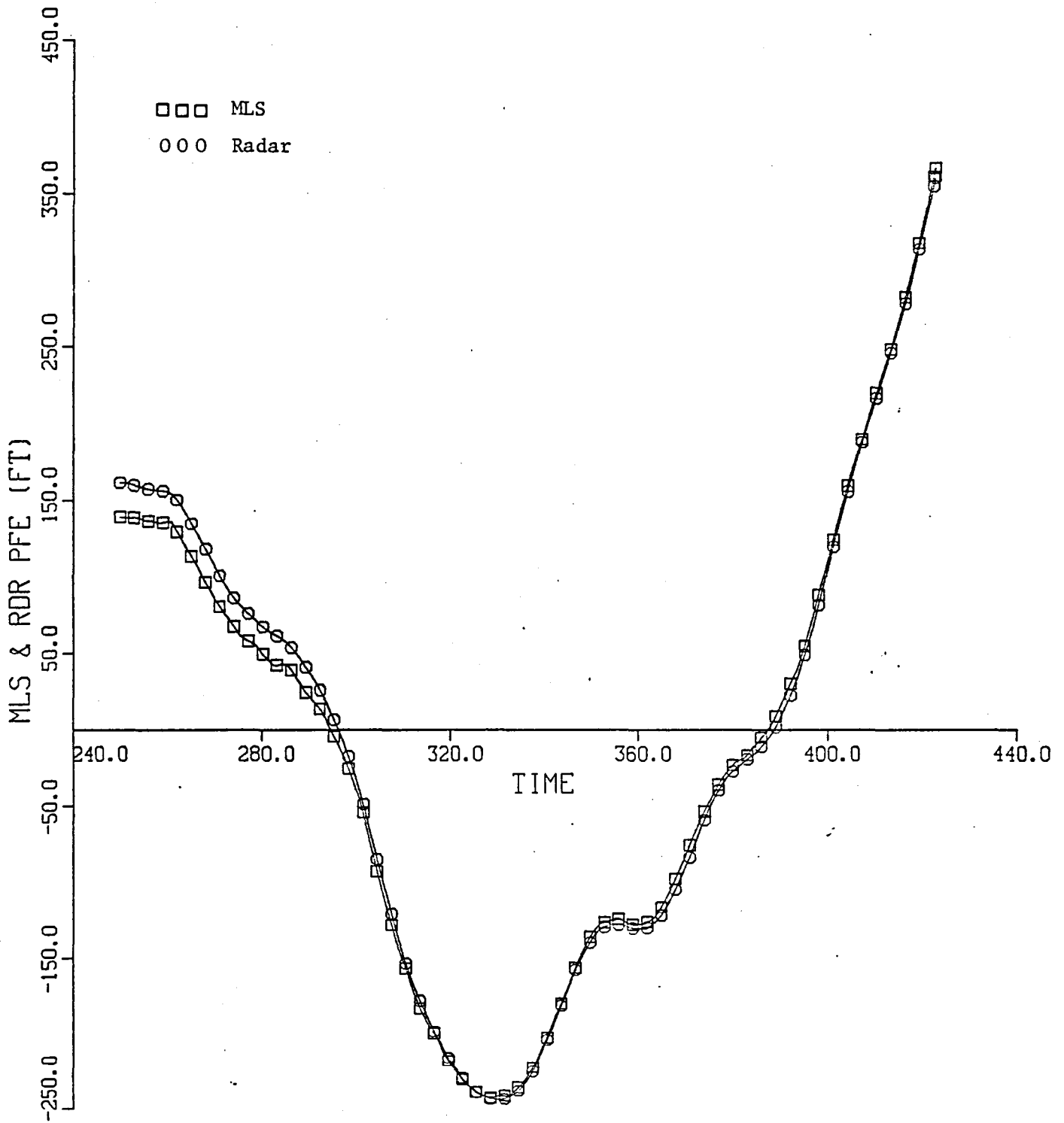
MLS & RDR PFE (FT)

Figure 12. MLS (MPFE) and Radar (RPFE) Path Following Error

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Histogram of r_{NSE} is shown in Fig. 13, which indicates that r_{NSE} is Gaussian with a bias b = 0.1 feet and a standard deviation σ_n = 5.9 feet. The sample autocovariance function of r_{NSE} is shown in Fig. 14. The navigation system error r_{NSE} may be modeled as a Gauss-Markov process as shown in Fig. 15.

$$G(s) = G_p(s) \; G_n(s)$$
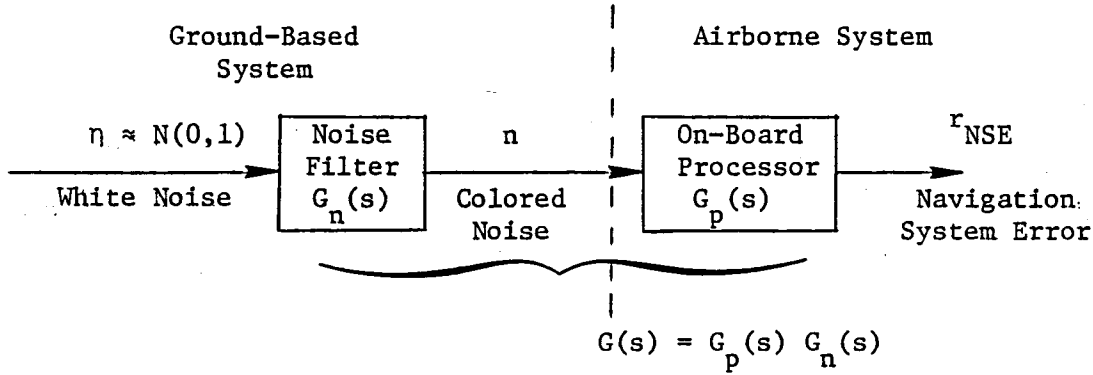
Figure 15. Gauss-Markov Noise Model

Note that the navigation system error r_{NSE} is obtained by "passing" normalized white noise η through two filters; a filter $G_n(s)$ corresponding to the ground-based LGS characteristics and a filter $G_p(s)$ reflecting the on-board processing of raw MLS data. However, given r_{NSE} alone, only the combined filter transfer function G(s) can be identified.

Autoregressive-Moving Average Modeling of r_{NSE}

The approach taken in this study is to model r_{NSE} as an autoregressive-moving average (ARMA) process. A general ARMA (p,q) progess is defined by:

$$z_t = \sum_{i=1}^{p} \phi_i \, z_{t-i} + a_t + \sum_{i=1}^{q} \theta_i \, a_{t-i} + \mu \qquad (1)$$

where the a_i are a normally distributed white noise sequence with mean 0 and variance σ_a^2. μ is the mean of the process z_t (i.e. r_{NSE}).

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Figure 13. Histogram of r_{NSE} of Figure 7

MLS AUTOCOVARIANCE

Figure 14.   Autocovariance Function of r_{NSE} of Figure 7 and of
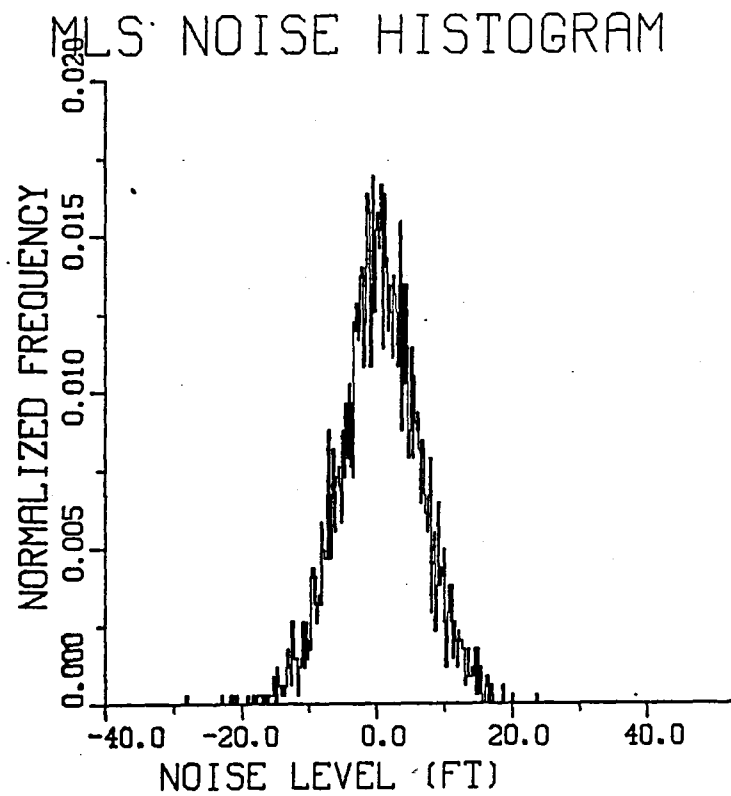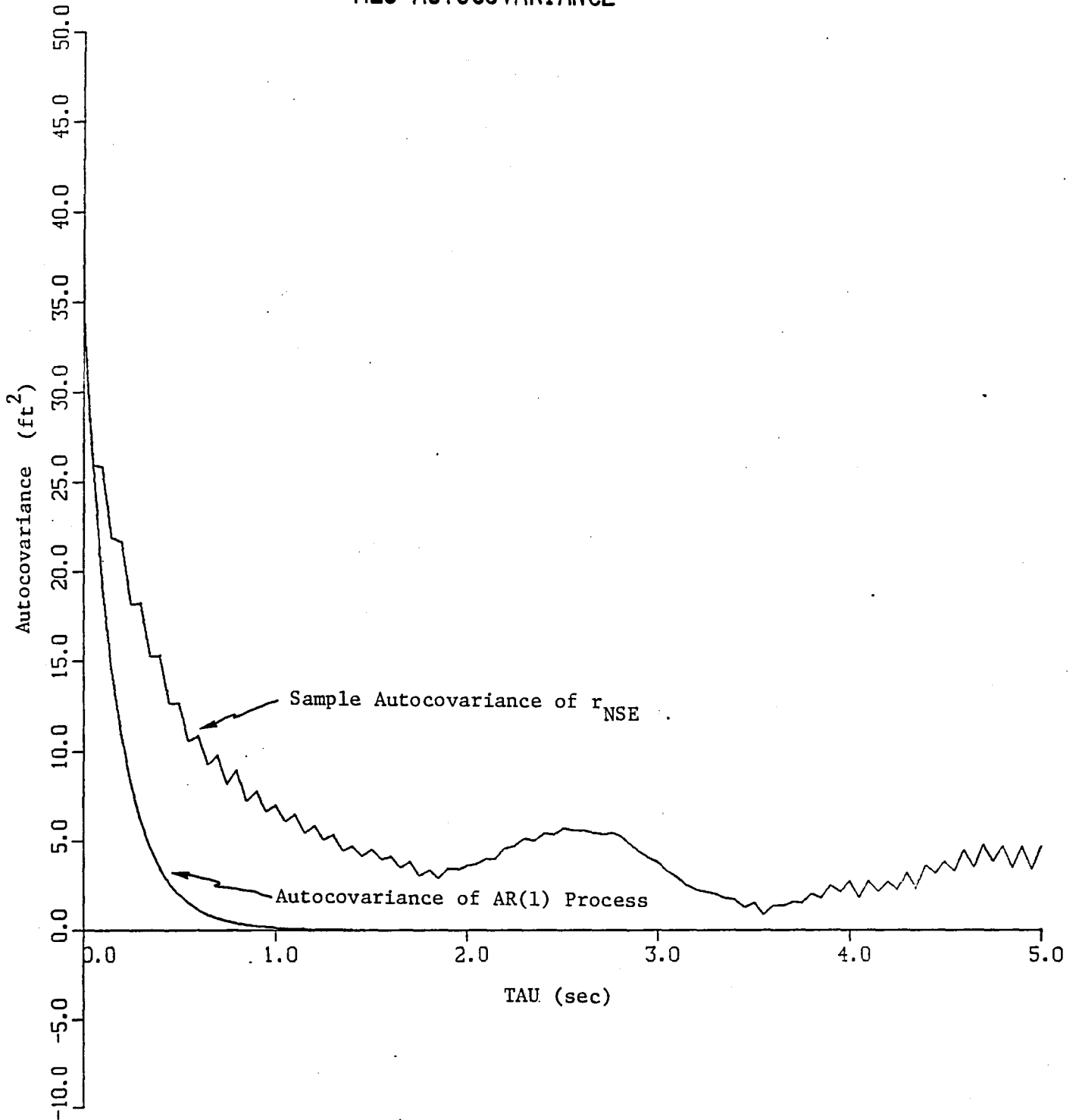   AR(1) Process with ϕ = .7153 (Maximum Likelihood Estimate)

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Software from the International Mathematics and Statistics Library (IMSL) was used to identify the parameters ϕ_i, θ_i, μ and σ_a^2 using a maximum likelihood procedure [1]. The pertinent program FTMXL from the IMSL package requires as input the order (p) of the AR and the order (q) of MA processes. In addition, the user may give initial estimates of the AR (ϕ_i, i=1 ... p) and MA (θ_i, i=1 ... q) parameters. The program then uses an iterative search technique to obtain the maximum likelihood estimates of the parameters of the process described by (1).

The MLS range NSE (r_{NSE}) was used as input data to the program FTMXL for identification of the ARMA parameters. Two different models were considered:

(1) First order autoregressive (AR) process

A first order AR process is defined by:

$$z_t = \phi z_{t-1} + a_t + \mu \tag{2}$$

An initial estimate of ϕ can be obtained from the autocovariance of the r_{NSE} data:

$$\phi^\circ = \frac{\gamma(1)}{\gamma(0)} \tag{3}$$

$$\text{where} \quad \gamma(r) = \frac{1}{N-r} \sum_{n=1}^{n-r} r_{NSE}(n)\, r_{NSE}(n+r) \qquad r = 0,1,\ldots m \tag{4}$$

For the data considered in this study, $\phi^\circ = 0.753$. Using this as an initial estimate, the program FTMXL results in the following identified model parameters:

$$\phi = .7513$$
$$\mu = .1137$$
$$\sigma_a^2 = 14.92$$

Figure 14 shows the autocovariance of the measured data and of the AR process as identified by FTMXL. The results clearly indicate that the first order AR process does not adequately model the MLS navigation system error (r_{NSE}) for lags greater than about 0.1 seconds.

The maximum likelihood technique for a first order AR process computes the pole ϕ in order to fit the autocovariance (equivalently the auto-correlation) for lags r=0 and r=1. Clearly, this may result in a poorer autocovariance fit for r>1 when the process being modeled is not AR(1) (Fig. 14). A better fit of the autocovariance function is obtained by choosing ϕ = .9. Figure 16 shows the autocovariance of the measured data (r_{NSE}) and of an AR(1) model with ϕ = .9. The figure shows that with ϕ = .9 the model autocovariance matches more closely the autocovariance of the measured data for a lag up to 1 second than the maximum likelihood (ϕ = .7513) covariance results (Fig. 14).

Maximum likelihood techniques generate AR(p) parameters using auto-correlations up to lag r=p. New techniques [2], recommend taking auto-correlations of lags r>p in order to estimate the AR parameters. These new techniques do not seem to demonstrate the parameter hypersensitivity seen in the classical Yule-Walker type algorithms.

(2) Second order ARMA (2,1) process

Program FTMXL was used to model r_{NSE} as an ARMA (2,1) process:

$$z_t = \phi_1 z_{t-1} + \phi_2 z_{t-2} + a_t + \theta_1 a_{t-1} + \mu \qquad (5)$$

The initial estimates for the parameters were obtained by discretizing an equivalent continuous ARMA(2,1) process [3]:

$$\phi_1^o = 1.86$$

$$\phi_2^o = -.87$$

$$\theta_1^o = .53$$

FTMXL converged to:

$$\phi_1 = 1.6060$$

$$\phi_2 = -.6142$$

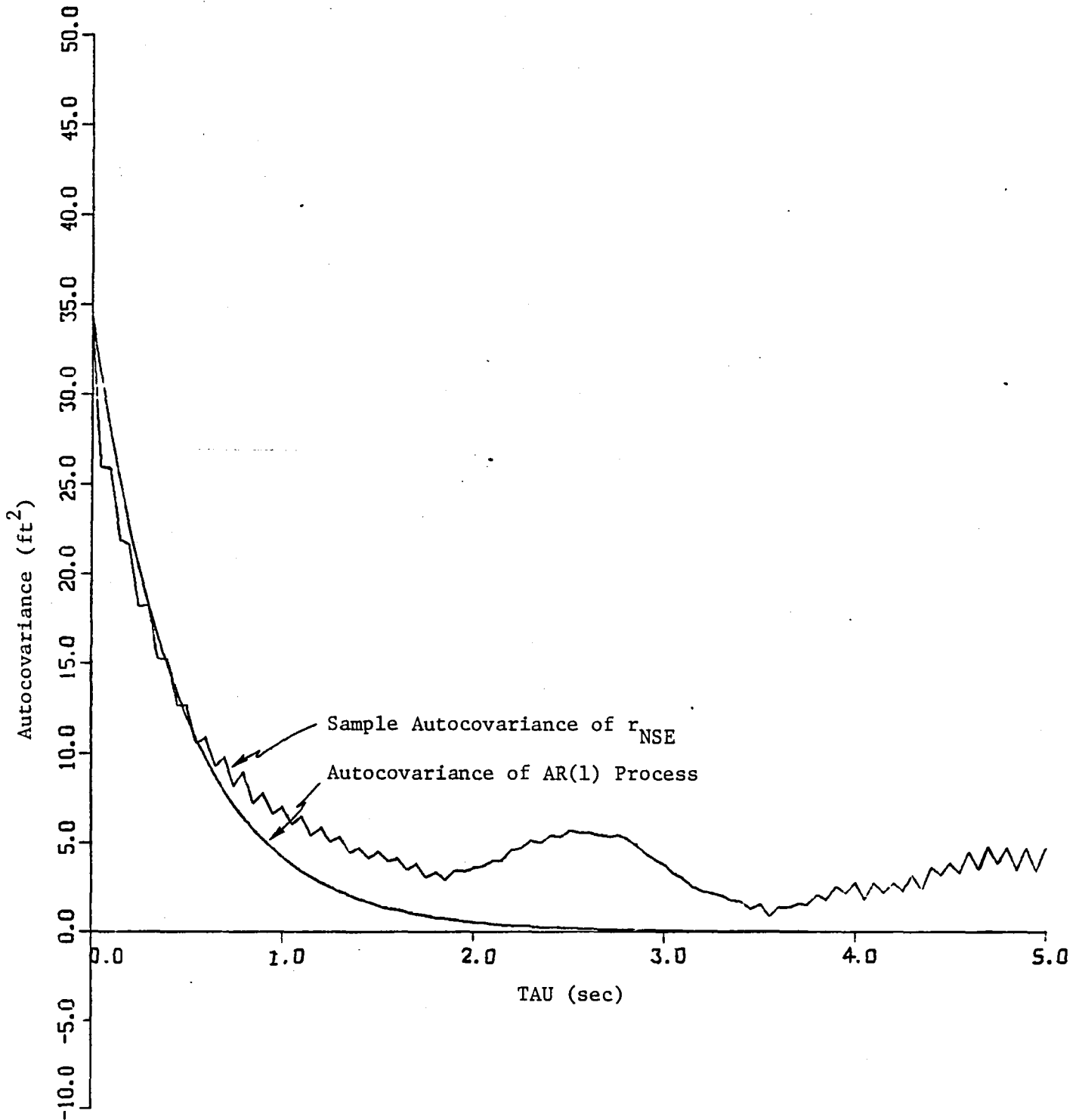$$\theta_1 = .9111$$

AUTOCOVARIANCE FUNCTIONS

Figure 16. Autocovariance Function of r_{NSE} and of AR(1) Process with $\phi = .9$

$$\mu \quad = \quad .0036$$

$$\sigma_a^2 \quad = \quad 14.28$$

Figure 17 shows the autocovariance of the ARMA(2,1) process super-imposed on the autocovariance of r_{NSE}. The figure shows that the auto-covariance of the ARMA(2,1) model is a better fit to the observed data for lag greater than 1 second as compared to the AR(1) model (Fig. 14). It is conceivable that an ARMA(3,1) model would closely match the data over all lags.

The results above incidate the need to apply systematic model struc-ture/parameter idenfication techniques to the observed MLS range NSE (r_{NSE}). This was considered to be beyond the scope of the current study.

AUTOCOVARIANCE FUNCTIONS
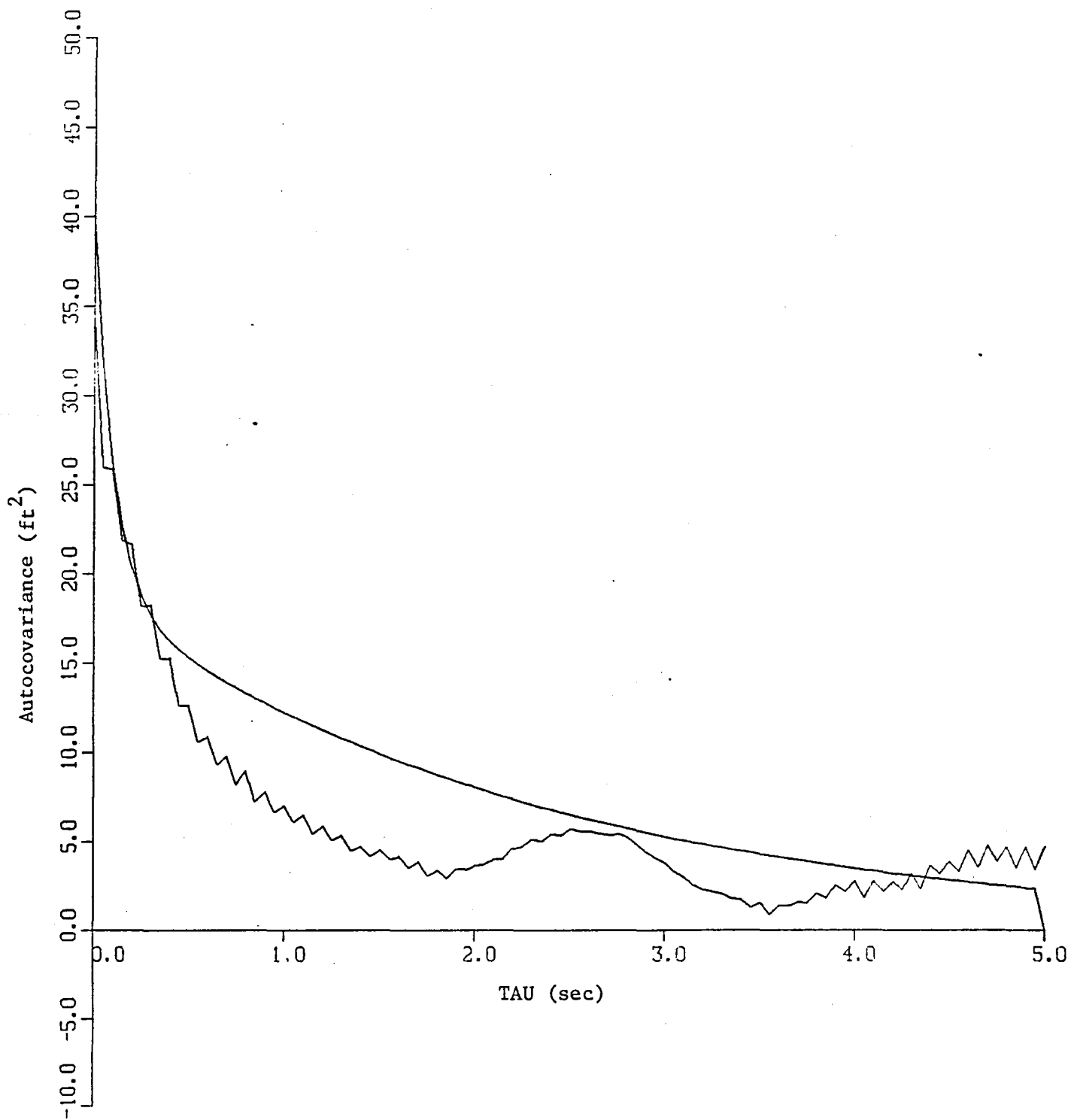
Figure 17.   Autocovariance Function s of r_{NSE} and of AR(2,1) Process

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CONCLUDING REMARKS

A preliminary analysis of the MLS range data indicates that the navigation system noise is Gaussian and may be represented as an auto-regressive – moving average (ARMA) process. The data available for this study was already filtered by an on-board digital processor. Further research with MLS raw unfiltered signals (range, azimuth and elevation) using systematic model structure determination and parameter identification methods is recommended.

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1. Box, G.E.P. and Jenkins, G.M., "Time Series Analysis, Forecasting and Control," Holden-Day, 1970.

2. Cadzow, J.A., "ARMA Modeling of Time Series," IEEE Transactions on Pattern Analysis and Machine Itelligence, Vol. PAMI-4, #2, March 1982.

3. Phadke, M.S., "Multiple Time Series Modeling and System Identification with Applications," Ph. D. Thesis, University of Wisconsin, 1973.

APPENDIX

PFE AND CMN FILTERS

Path Following Error Filter (PFEF)

$$G_{PFEF}(s) \quad = \quad \frac{\omega_n^2}{s^2 + 2\zeta\omega_n s + \omega_n^2} \quad : \quad \text{Low-Pass}$$

$$\zeta = 1. \quad , \quad \omega_n = \frac{1}{.64}\omega_o$$

Control Motion Noise Filter (CMNF)

$$G_{CMNF}(s) \quad = \quad \frac{s}{s + \omega_1} \qquad : \quad \text{High-Pass}$$

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15. Supplementary Notes

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(415) 965-5425 or FTS 448-5425

16. Abstract

Flight test data was used to develop a methodology for modeling MLS range navigation system errors (r_{NSE}). The data used corresponded to the constant velocity and glideslope approach segment of a helicopter landing trajectory. The MLS range measurement was assumed to consist of low frequency and random high frequency components. The random high frequency component was extracted from the MLS range measurements. This was done by appropriate filtering of the range residual generated from a linearization of the range profile for the final approach segment. This range navigation system error (r_{NSE}) was then modeled as an autoregressive-moving average (ARMA) process. Maximum likelihood techniques were used to identify the parameters of the ARMA process.

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