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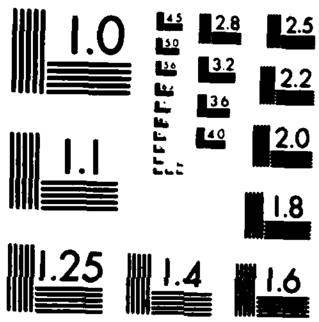


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# A Summary of Results in Data Adaptive Detection and Estimation

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April 1983



**Prepared for**

**OFFICE OF NAVAL RESEARCH (Code 411 SP)**
**Statistics and Probability Branch**
**Arlington, Virginia 22217**
**under Contract N00014-81-K-0144**
**D. W. Tufts, Principal Investigator**



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| 1. REPORT NUMBER | 2. GOVT ACCESSION NO. AD-A128868 | 3. RECIPIENT'S CATALOG NUMBER |
| 4. TITLE (and Subtitle) A Summary of Results in Data Adaptive Detection and Estimation | | 5. TYPE OF REPORT & PERIOD COVERED |
| | | 6. PERFORMING ORG. REPORT NUMBER |
| 7. AUTHOR(s) Steven Kay | | 8. CONTRACT OR GRANT NUMBER(s) N00014-81-K-0144 |
| 9. PERFORMING ORGANIZATION NAME AND ADDRESS Department of Electrical Engineering, University of Rhode Island, Kingston, Rhode Island 02881 | | 10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS |
| 11. CONTROLLING OFFICE NAME AND ADDRESS Office of Naval Research (Code 411 SP) | | 12. REPORT DATE |
| | | 13. NUMBER OF PAGES 15 |
| 14. MONITORING AGENCY NAME & ADDRESS (if different from Controlling Office) | | 15. SECURITY CLASS. (of this report) Unclassified |
| | | 15a. DECLASSIFICATION/DOWNGRADING SCHEDULE |

16. DISTRIBUTION STATEMENT (of this Report)

Approved for public release; distribution unlimited

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

18. SUPPLEMENTARY NOTES

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

This report describes a number of results which have been obtained in the Data Adaptive Detection and Estimation project. The various papers summarized deal with properties of autoregressive representations as they relate to detection and estimation in partially known signal and/or noise environments. Complete copies of the works can be obtained from the author.

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# A Summary of Results in Data Adaptive Detection and Estimation

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## Abstract

This report describes a number of results which have been obtained in the Data Adaptive Detection and Estimation project. The various papers summarized deal with properties of autoregressive representations as they relate to detection and estimation in partially known signal and/or noise environments. Complete copies of the works can be obtained from the author.

## SUMMARY

1) "On the Statistics of the Estimated Reflection Coefficients of an Autoregressive Process" (with John Makhoul of Bolt, Beranek, and Newman)--submitted to IEEE Trans. on Acoustics, Speech, and Signal Processing.

This paper derives a recursive means of computing the Cramer-Rao (CR) lower bound for the estimated reflection coefficients of an autoregressive (AR) process. The exact algorithm which computes the bound is given in Figure 1. Since the CR bound is attained asymptotically (for large data records) for a Maximum Likelihood Estimate of the reflection coefficients, one can also use the algorithm of Figure 1 to describe the statistics of the MLE. It is also shown in this paper that all currently available estimators for the reflection coefficients are MLE's for large data records. Thus, the results can be used to statistically characterize these estimators, i.e., the Burg algorithm[1] as an example. An example of the actual covariance matrix (obtained via computer simulation) and the CR bound is shown in Figure 2. The data length was 1000 points.

2) "Simple Proofs of the Minimum Phase Property of the Prediction Error Filter" (with Louis Pakula of U.R.I.)--IEEE Trans. on Acoustics, Speech, and Signal Processing, April 1983.

Presented are two simple proofs which assert the well known property that all the zeros of the optimal prediction error filter lie on or within the unit circle of the Z plane. The first proof is somewhat incomplete in that it only shows that the zeros lie on or within the unit circle. It gives no indication as to when the zeros must be totally within the unit circle. However, it is extremely simple. The second proof which is slightly more complex also determines conditions under which the zeros may be on the unit circle.

3) "Recursive Maximum Likelihood Estimation of Autoregressive Processes"--IEEE Trans. on Acoustics, Speech, and Signal Processing, February 1982.

An estimation algorithm is derived which is a closer approximation to the true MLE of the parameters of an AR process than currently existing procedures. Specifically, the algorithm does not make the standard assumption that the determinant of the filter covariance matrix can be neglected in the maximization of the likelihood function. This common assumption is not valid for short data records and/or highly peaked spectra. By incorporating the determinant and maximizing the likelihood function recursively (in model order) more accurate parameter and spectral estimates are obtained. The algorithm is summarized in Figure 3. Also, Figure 4 summarizes some simulation results which verify the improved performance of the algorithm for short data records. (RMLE = Recursive MLE, FB = Forward-Backward, YW = Yule-Walker).

4) "More Accurate Autoregressive Parameter and Spectral Estimates for Short Data Records"--IEEE Workshop on Spectral Estimation, Hamilton, Ontario, August 1981.

This paper is a shortened version of 3.

5) "Some Results in Linear Interpolation Theory"--to be published in IEEE Trans. on Acoustics, Speech, and Signal Processing.

The optimal finite length interpolation filter for a wide sense stationary process is derived. It is shown that for an AR process one can significantly reduce the power out of an FIR filter by performing interpolation rather than the more common one sided prediction. Also, the optimal interpolation filter for an AR process, i.e., the one which minimizes the interpolation error power, is found to be the one which attempts to interpolate at the midpoint of a data record. This result although intuitive is shown not to hold for more general processes. Finally, some well known results in infinite length FIR filter interpolation are simply derived using AR approximations of infinite order.

6) "Accurate Frequency Estimation at Low Signal-to-Noise Ratios"--submitted to IEEE Trans. on Acoustics, Speech, and Signal Processing.

An iterative algorithm for frequency estimation of sinusoids in white noise is described and analyzed. The algorithm iteratively computes AR parameter estimates after the original data has been filtered by an all pole filter. The algorithm is shown to be related to the Steiglitz-McBride algorithm[2]. It is summarized in Figure 5, where it has been termed the Iterative Filtering Algorithm (IFA). For two sinusoids closely spaced in frequency the algorithm performance is shown in Figure 6. Also, shown is the CR bound (for unbiased estimators) and the principal component (PC) approach of Tufts and Kumaresan[3]. The IFA outperforms the PC approach at low SNR's. The PC approach had been claimed to offer the best performance other than a direct MLE, at low SNR's. At higher SNR's a bias is present which tends to degrade the performance of the IFA. In Figure 7 a comparison is made with a direct MLE, which amounts to a nonlinear least squares estimator. Again at low SNR the IFA appears to perform better.

7) "Asymptotically Optimal Detection in Unknown Colored Noise via Autoregressive Modeling"--to be published in IEEE Trans. on Acoustics, Speech, and Signal Processing.

The problem of detecting a known signal in Gaussian noise of unknown covariance is addressed. The noise is assumed to be an AR process of known order but unknown coefficients. Thus, the parameterization of the covariance leads to a problem in composite hypothesis testing. Since in general no uniformly most powerful test exists, the Generalized Likelihood Ratio

Test (GLRT) is applied. The GLRT detector which results is shown in Figure 8. As expected adaptive prewhiteners are included which assume either the signal is present (upper channel) or absent (lower channel). The detector is not a single estimated prewhitener and matched filter as might be expected. The performance of the detector is shown in Figures 9 and 10 for an AR process of order $p=1$ and parameter $a=-0.9$ and for various data record lengths $N=20,100$. The optimal curve is the performance assuming a known covariance function, i.e., a prewhitener and matched filter. It is seen that even for short data records the performance is nearly optimal. Finally, it is proven that for large data records the GLRT performance is equal to that of a prewhitener (assuming a known covariance) and matched filter and hence is optimal.

8) "Detection for Active Sonars via Autoregressive Modeling,"--Workshop on Maximum Entropy and Bayesian Methods in Applied Statistics, University of Wyoming, Laramie, Wyoming, August 1982.

This paper is a shortened version of 7.

1) For n=1

$$\underline{a}_1 = a_1(1) = K_1$$

$$\underline{A}_1 = \underline{B}_1 = \underline{E}_1 = \sigma_0^2 = 1$$

$$\sigma_1^2 = (1-K_1^2)$$

$$\underline{C}_{\hat{K}}(1) = \frac{1}{N}(1-K_1^2)$$

2) $n \leftarrow n+1$

$$\sigma_n^2 = (1-K_n^2)\sigma_{n-1}^2$$

$$\underline{D}_{n-1} = \frac{1}{1-K_n^2}\underline{A}_{n-1}(\underline{I}-K_n\underline{J})\underline{B}_{n-1}$$

$$\underline{C}_{\hat{K}}(n) = \frac{1}{N}\begin{bmatrix} \sigma_n^2 \underline{D}_{n-1}\underline{E}_{n-1}^{-1}\underline{D}_{n-1}^T & \underline{0} \\ \underline{0}^T & 1-K_n^2 \end{bmatrix}$$

3) If n=p, let $\underline{C}_{\hat{K}} = \underline{C}_{\hat{K}}(n)$ and exit.

4)

$$\underline{E}_n^{-1} = \begin{bmatrix} \underline{E}_{n-1}^{-1} & \underline{0} \\ \underline{0}^T & 1/\sigma_n^2 \end{bmatrix}$$

$$\underline{a}_{n-1} = \begin{bmatrix} (\underline{I}+K_{n-1}\underline{J})\underline{a}_{n-2} \\ K_{n-1} \end{bmatrix}$$

$$B_n = \begin{bmatrix} \underline{B}_{n-1} & \underline{J}\underline{a}_{n-1} \\ \underline{0}^T & 1 \end{bmatrix}$$

$$\underline{A}_n = \begin{bmatrix} \frac{1}{1-K_n^2}\underline{A}_{n-1}(\underline{I}-K_n\underline{J}) & -\frac{1}{1-K_n^2}\underline{A}_{n-1}(\underline{I}-K_n\underline{J})\underline{J}\underline{a}_{n-1} \\ \underline{0}^T & 1 \end{bmatrix}$$

5) Go to 2

Note that $\underline{0}^T$ is $1\mathrm{x}(n-1)$.

Figure 1. Summary of Cramer-Rao Bound Computation for Reflection Coefficients.

TABLE 2

| | TRUE VALUES | | | ESTIMATED VALUES | | |
|---|---|---|---|---|---|---|
| $K_1$ $K_2$ $K_3$ | 0.570 | 0.570 | 0.570 | 0.569 | 0.568 | 0.564 |
| | 0.541 | − 0.490 | 0.000 | 0.523 | − 0.479 | − 0.006 |
| $NC_{\hat{K}}$ | − 0.490 | 0.675 | 0.000 | − 0.479 | 0.689 | 0.028 |
| | 0.000 | 0.000 | 0.675 | − 0.006 | 0.028 | 0.665 |

| | TRUE VALUES | | | ESTIMATED VALUES | | |
|---|---|---|---|---|---|---|
| $K_1$ $K_2$ $K_3$ | 0.570 | − 0.570 | 0.570 | 0.557 | − 0.563 | 0.563 |
| | 7.210 | − 1.790 | 0.000 | 6.988 | − 1.858 | − 0.151 |
| $NC_{\hat{K}}$ | − 1.790 | 0.675 | 0.000 | − 1.858 | 0.716 | 0.016 |
| | 0.000 | 0.000 | 0.675 | − 0.151 | 0.016 | 0.692 |

Figure 2. True and estimated values of the reflection coefficients and their covariances for two AR(3) processes. The two processes differ by the sign of $K_2$.

$$\mathcal{E}_0 = S_{00}$$

for $n = 1$: $C_n = S_{01}$, $d_1 = S_{11}$

to find $K_1$ solve

$$K_1^3 + \frac{N-2}{N-1}\frac{C_1}{d_1}K_1^2 - \frac{\mathcal{E}_0 + Nd_1}{(N-1)d_1} - \frac{N}{N-1}\frac{C_1}{d_1} = 0$$

and choose root within $[-1, 1]$.

$$a_1^{(1)} = K_1$$

$$\mathcal{E}_1 = S_{00} + 2K_1S_{01} + K_1^2 S_{11}$$

$$\sigma_\epsilon^{2(1)} = \frac{1}{N}\mathcal{E}_1$$

For $n = 2, 3, \cdots, p$:

$$C_n = a_{n-1}'^T \begin{bmatrix} q_{n-1}^T & S_{0n} \\ S_{n-2} & p_{n-1} \end{bmatrix} b_{n-1}'$$

$$d_n = b_{n-1}'^T \begin{bmatrix} S_{n-2} & p_{n-1} \\ p_{n-1}^T & S_{nn} \end{bmatrix} b_{n-1}'^T.$$

to find $K_n$ solve (for $d_n > 0$)*

$$K_n^3 + \frac{N-2n}{N-n}\frac{C_n}{d_n}K_n^2 - \frac{n\mathcal{E}_{n-1} + Nd_n}{(N-n)d_n} - \frac{N}{N-n}\frac{C_n}{d_n} = 0$$

and choose root within $[-1, 1]$.

$$a_i^{(n)} = \begin{cases} a_i^{(n-1)} + K_n a_{n-i}^{(n-1)}, & i = 1, 2, \cdots, n-1 \\ K_n, & i = n \end{cases}$$

$$\mathcal{E}_n = \mathcal{E}_{n-1} + 2C_nK_n + d_nK_n^2$$

$$\sigma_\epsilon^{2(n)} = \frac{1}{N}\mathcal{E}_n$$

where

$$a_{n-1}' = [1 \quad a_1^{(n-1)} \quad a_2^{(n-1)} \cdots a_{n-1}^{(n-1)}]^T$$

$$b_{n-1}' = [a_{n-1}^{(n-1)} \quad a_{n-2}^{(n-1)} \cdots a_1^{(n-1)} \quad 1]^T$$

$$[S_n]_{ij} = S_{ij} = \sum_{t=1}^{N-i-j} x_{t+i}x_{t+j} \qquad \begin{matrix} i = 0, 1, \cdots, n \\ j = 0, 1, \cdots, n \end{matrix}$$

$$S_n = \begin{bmatrix} \underset{1\times 1}{S_{00}} & \underset{1\times(n-1)}{q_{n-1}^T} & \underset{1\times 1}{S_{0n}} \\ \underset{(n-1)\times 1}{q_{n-1}} & \underset{(n-1)\times(n-1)}{S_{n-2}} & \underset{(n-1)\times 1}{p_{n-1}} \\ \underset{1\times 1}{S_{n0}} & \underset{1\times(n-1)}{p_{n-1}^T} & \underset{1\times 1}{S_{nn}} \end{bmatrix}$$

*For $d_n < 0$ see Section III for discussion of roots.

Figure 3. Summary of Recursive MLE Algorithm.

**TABLE I**

COMPARISON OF AR PARAMETER ESTIMATION METHODS

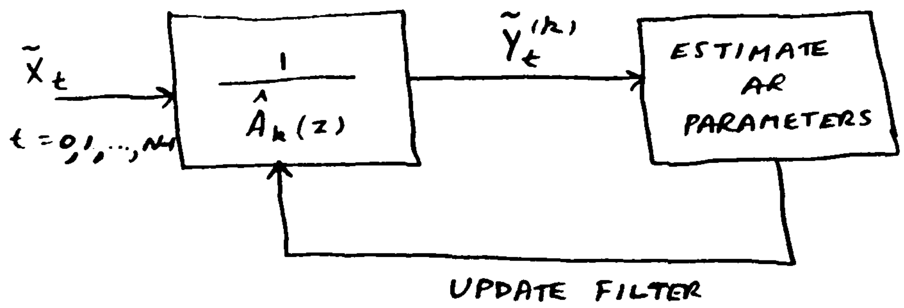
$N$ = 11 Data Points

| | $a_1$ | $a_2$ | $a_3$ | $a_4$ |
|---|---|---|---|---|
| True AR Parameters | -2.76070 | 3.81060 | -2.65350 | 0.92380 |
| Mean–YW | -1.01527 | 0.61949 | 0.04466 | 0.05735 |
| Mean–FB | -2.59333 | 3.42185 | -2.27303 | 0.77262 |
| Mean–RMLE | -2.62975 | 3.51086 | -2.37156 | 0.81412 |
| Variance–YW | 3.13780 | 10.29627 | 7.33884 | 0.75840 |
| Variance–FB | 0.11598 | 0.52574 | 0.49303 | 0.08462 |
| Variance–RMLE | 0.10960 | 0.33371 | 0.26227 | 0.04148 |

$N$ = 50 Data Points

| | $a_1$ | $a_2$ | $a_3$ | $a_4$ |
|---|---|---|---|---|
| True AR Parameters | 2.76070 | 3.81060 | -2.65350 | 0.92380 |
| Mean–YW | 1.30552 | 0.92378 | 0.05153 | 0.06719 |
| Mean–FB | 2.72368 | 3.71024 | -2.54984 | 0.87639 |
| Mean–RMLE | 2.71515 | 3.69876 | -2.54345 | 0.87765 |
| Variance–YW | 2.22544 | 8.56804 | 6.90835 | 0.74526 |
| Variance–FB | 0.00758 | 0.04138 | 0.04219 | 0.00858 |
| Variance–RMLE | 0.01076 | 0.04485 | 0.04069 | 0.00741 |

Figure 4. Comparison of AR Parameter Estimation Methods




$$\hat{A}_k(z) = 1 + \sum_{n=1}^{p} \hat{a}_n^{(k)} z^{-n}$$

Figure 5 - Generic Iterative Filtering Algorithm

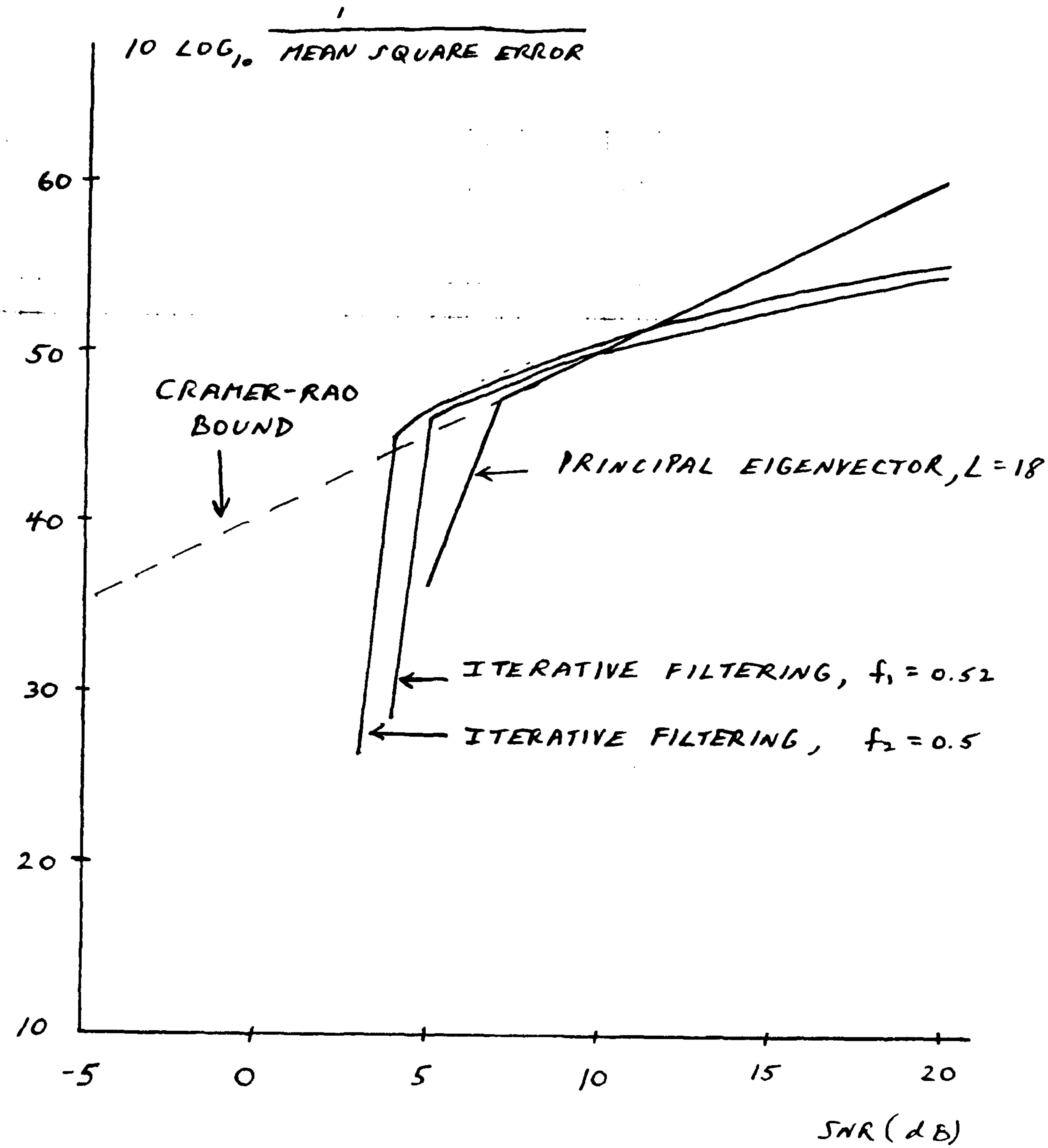



Figure 6. Comparison of Frequency Estimators,
$\varphi_1 = \pi/4$, $\varphi_2 = 0$

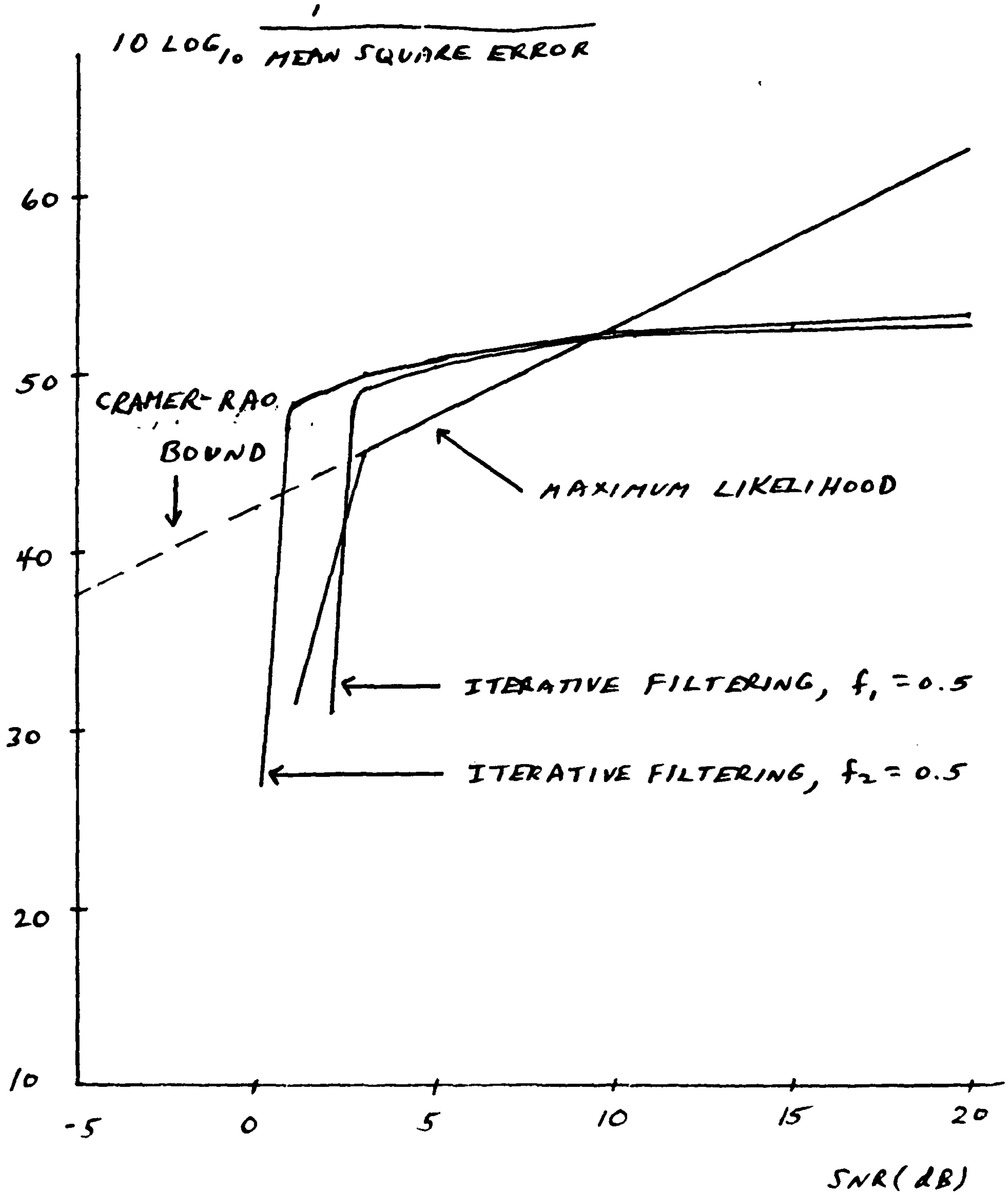
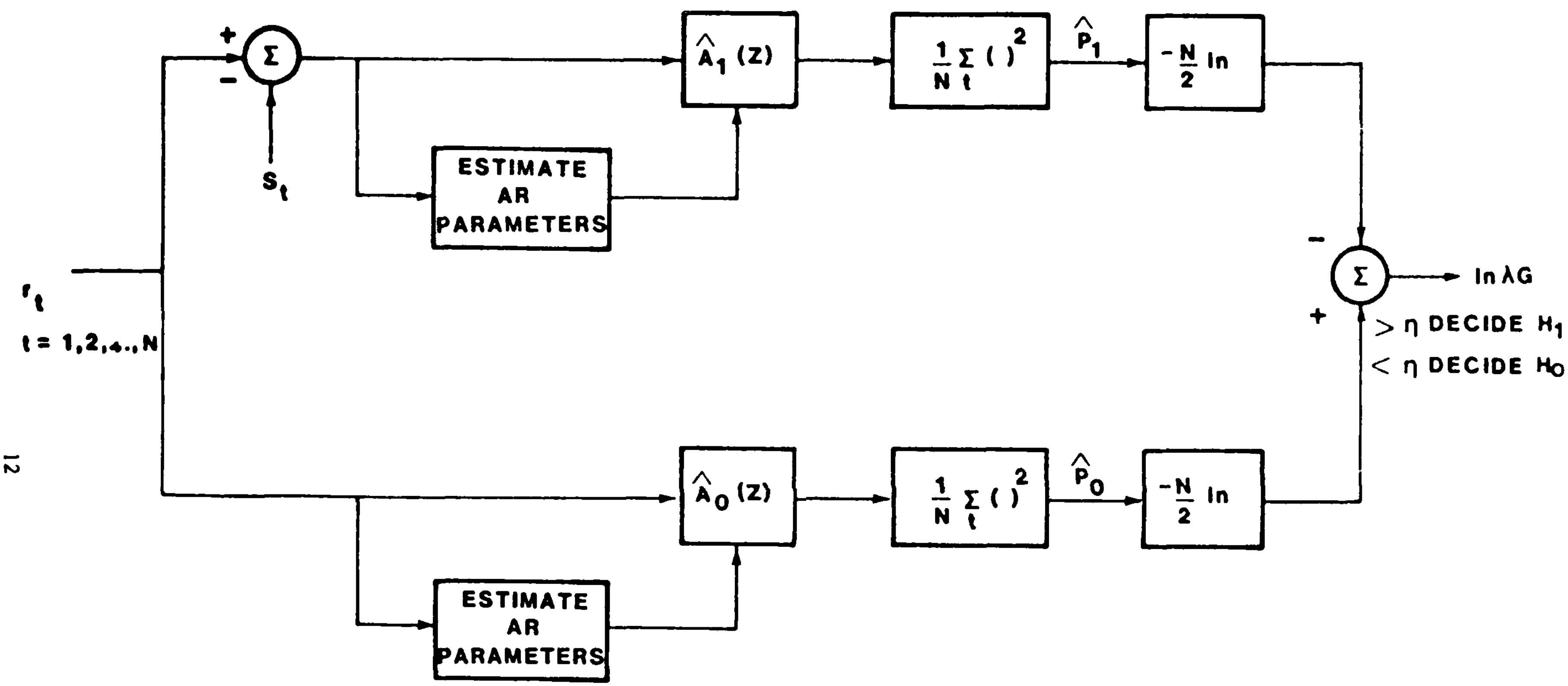



Figure 7. Comparison of Frequency Estimators,
$\varphi_1 = 0, \varphi_2 = 0$




**WHERE** $\hat{A}_i(Z) = 1 + \sum_{K=1}^{P} \hat{a}_{ik} Z^{-k}$ = **ESTIMATED PREWHITENER UNDER $H_i$**

Figure 8. Generalized Likelihood Ratio Test Detector

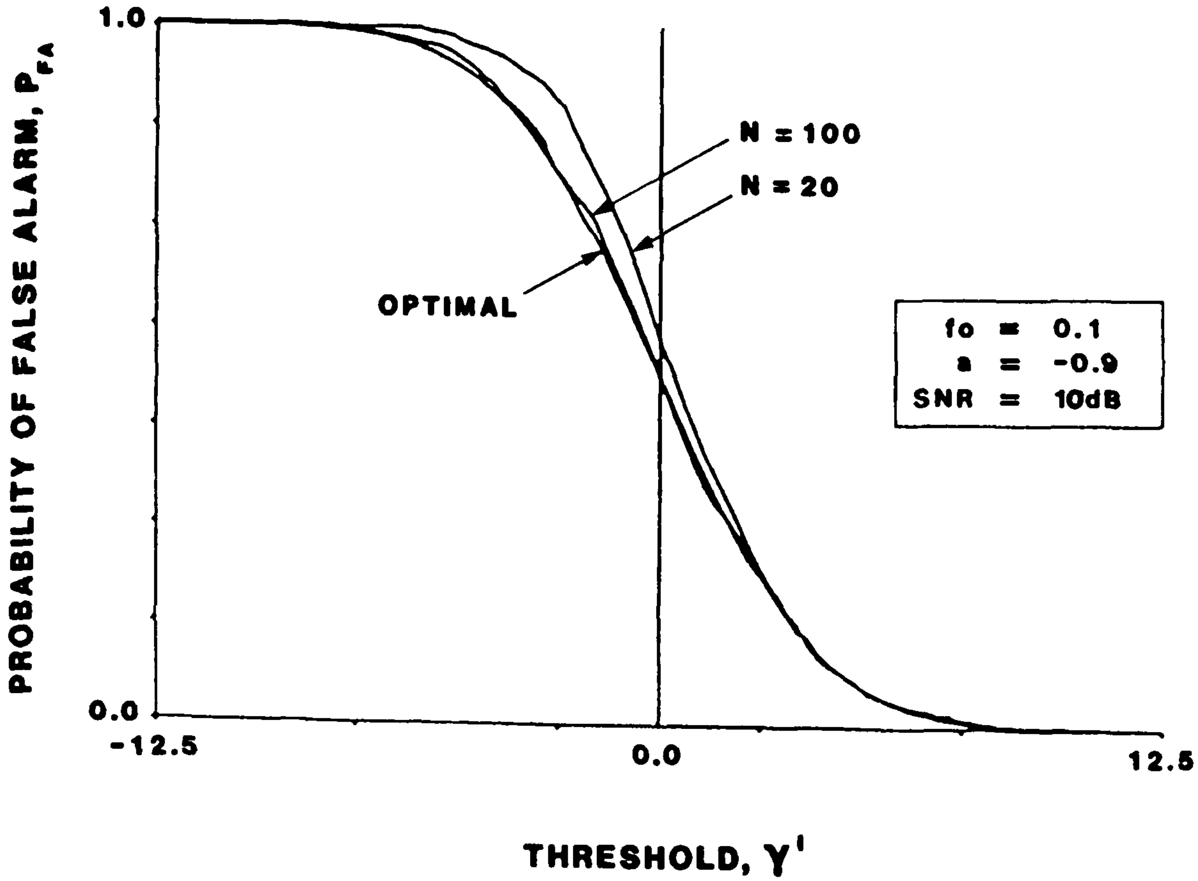



Figure 9. Probability of False Alarm of GLRT Detector

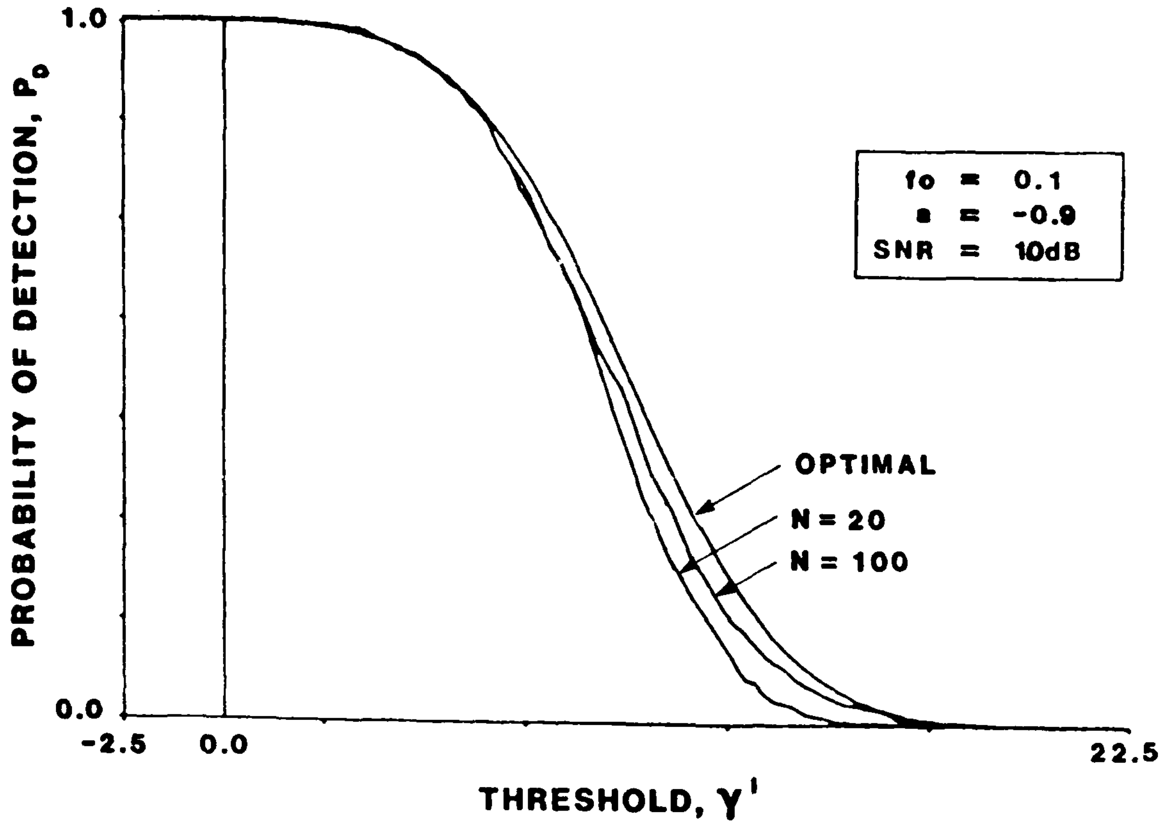



Figure 10. Probability of Detection of GLRT Detector

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