AD-A056 074 SOUTHEASTERN MASSACHUSETTS UNIV NORTH DARTMOUTH DEPT --ETC F/G 8/11
AN INTRODUCTION TO SEISMIC SIGNAL PROCESSING.(U)
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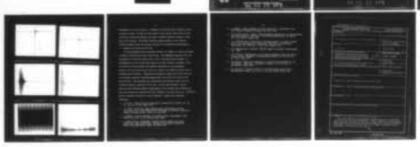

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TECHNICAL REPORT SERIES IN INFORMATION SCIENCES
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ELECTRICAL ENGINEERING DEPARTMENT

NORTH DARTMOUTH, MASS. 02747 U.S.A.

Grant AFOSR 76-2951
TR No. EE-78-3
June 8, 1978

14 EE-78-3

6 AN INTRODUCTION TO
SEISMIC SIGNAL PROCESSING

9 Technical rept.

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11 8 Jun 78

12 16p.

Abstract

This paper examines the fundamental problem areas and the available solutions in seismic signal processing. Topics considered include seismic signal modeling, spectral matching and the ARMA model, parameter estimation, homomorphic versus predictive deconvolution, Kalman filtering, and the measurement of the first arrival time.

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An Introduction to Seismic Signal Processing

C. H. Chen

1. Introduction

In recent years, computers have played an increasingly important role in seismic studies such as the petroleum exploration, nuclear detection, earthquake research and marine seismic studies. Computers are needed to process large volumes of seismic data from which useful information must be extracted accurately. A number of signal processing algorithms have been developed in recent years many of which are very useful for seismic data. Although the processing techniques vary with the nature of seismic data, an important problem in seismic signal processing is deconvolution. The received seismic data can be considered as the result of convolution between the source signal and the transmission medium plus the additive instrument noise. This paper will be concerned mainly with the deconvolution of such convolved signal as well as other seismic signal processing algorithms. This discussion is preceded by a study of seismic signal modeling as a good understanding of the seismic signal generation is much needed for effective signal processing.

2. Seismic Signal Modeling

Figures 1, 2, and 3 depict simplified transmission processes of seismic waves. Figure 1 shows an inhomogeneous earth excited by a deep source. The earth is bounded by two homogeneous infinite half-spaces, the air and the basement rock. Here the earth is a distributed parameter system governed by partial differential equations. For digital processing, the originally continuous velocity profile can be quantized and, as a result, the earth can now be modeled as a lumped paramter system. If the time of signal propagation through a layer is short compared with the duration of the signal, then the lumped parameter assumption is valid. By choosing the depth of each layer to be very small, i.e. considering many layers, we can satisfy the lumped parameter conditions.

To simplify the analysis, we can assume that the system of Fig. 1 is linear and time-invariant. Let a's represent the constant parameters associated with the

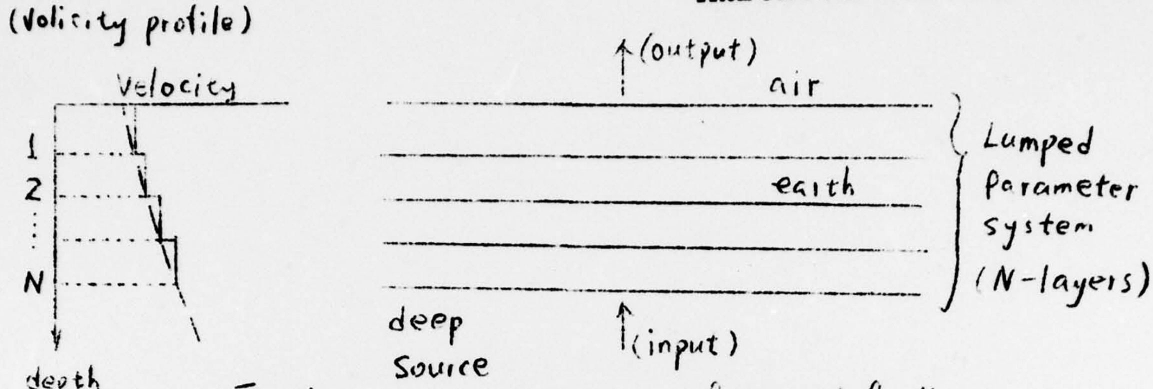


Fig. 1

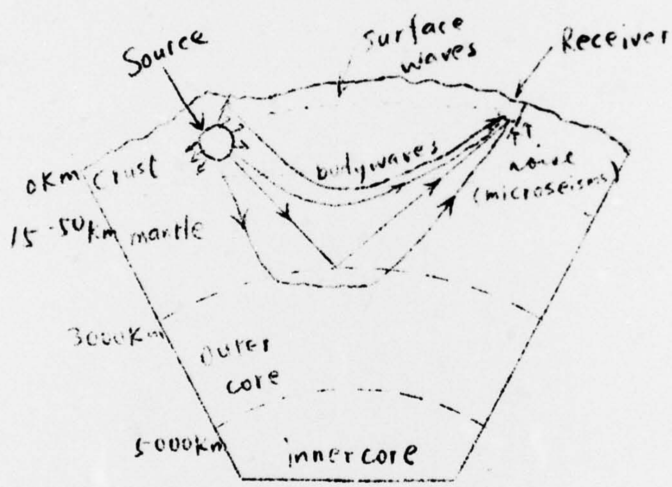


Fig. 2

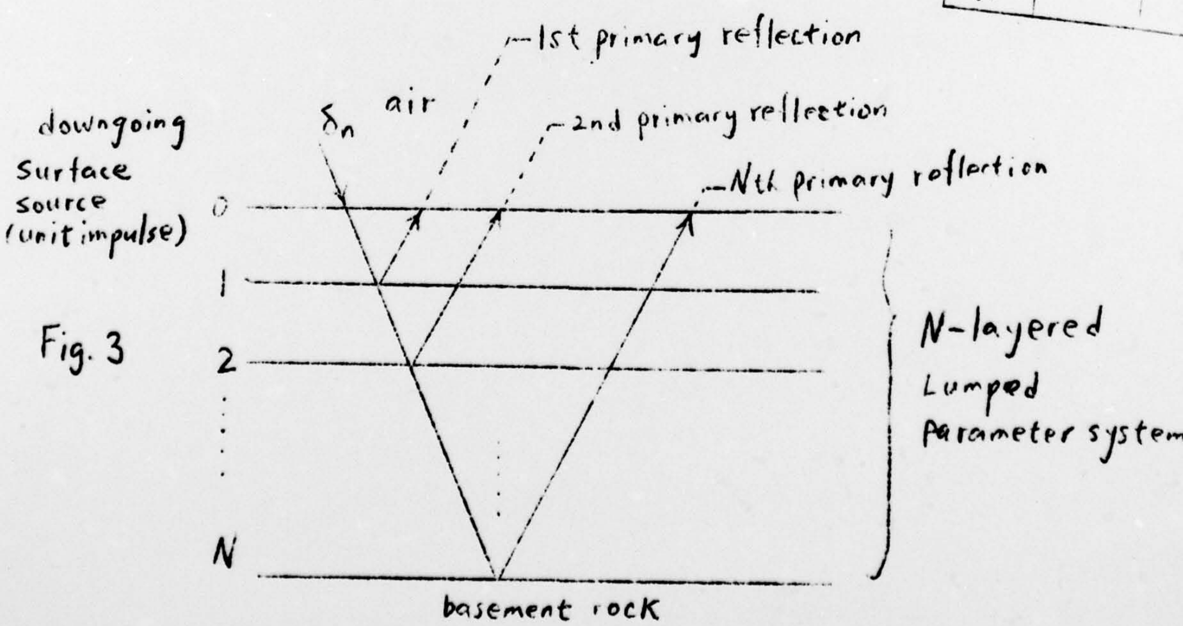


Fig. 3

N layers. Each layer causes a unit delay for the seismic wave. We can expect the input x_n and the output y_n to satisfy the linear difference equation,

$$y_n + a_1 y_{n-1} + \ldots + a_n y_{n-N} = x_n \qquad (1)$$

Taking z-transform on both sides of Eq. (1) we obtain the ratio,

$$\frac{Y(z)}{X(z)} = \frac{1}{1 + a_1 z^{-1} + a_2 z^{-2} + \ldots + a_N z^{-N}} = B(z) \qquad (2)$$

which represents the transfer function of an all-pole filter. Our physical claim that the lumped parameter model represents a stable system is equivalent to the mathematical condition that the transfer function contains no poles outside the unit circle. Equation (1) also represents an autoregressive model for the digitized seismic signal.

Figure 2 describes the transmission of teleseismic waves. A more appropriate model is given by Fig. 3 which shows internal primary reflections caused by a downgoing unit impulse δ_n applied at the surface. For clarity, ray paths are drawn at oblique incidence but wave-motion analysis is for normal incidence. Let b_n be the response of a single layer with respect to the unit impulse input δ_n. By linearity property, a delayed impulse δ_{n-m} gives rise to b_{n-m} and $C\delta_n$ gives rise to Cb_n where C is a constant. By superposition principle, the total impulse response can be written as

$$h_n = \varepsilon_1 b_{n-1} + \varepsilon_2 b_{n-2} + \ldots + \varepsilon_N b_{n-N} = \varepsilon_n * b_n \qquad (3)$$

where "*" denotes convolution and ε_n's are the hypothetical sources of strength given by the reflection coefficients r_n at various layers. Taking the z-transform of Eq. (3) we have

$$H(z) = E(z)B(z) = \frac{\varepsilon_1 z^{-1} + \varepsilon_2 z^{-2} + \ldots + \varepsilon_N z^{-N}}{1 + a_1 z^{-1} + a_2 z^{-2} + \ldots + a_N z^{-N}} \qquad (4)$$

which gives the transfer function of a normal-incidence reflection seismogram and is the ARMA model used in reflection seismology.

Since the layered system is assumed to be both linear and time invariant, then the reflection seismogram y_n due to an arbitrary source pulse s_n is

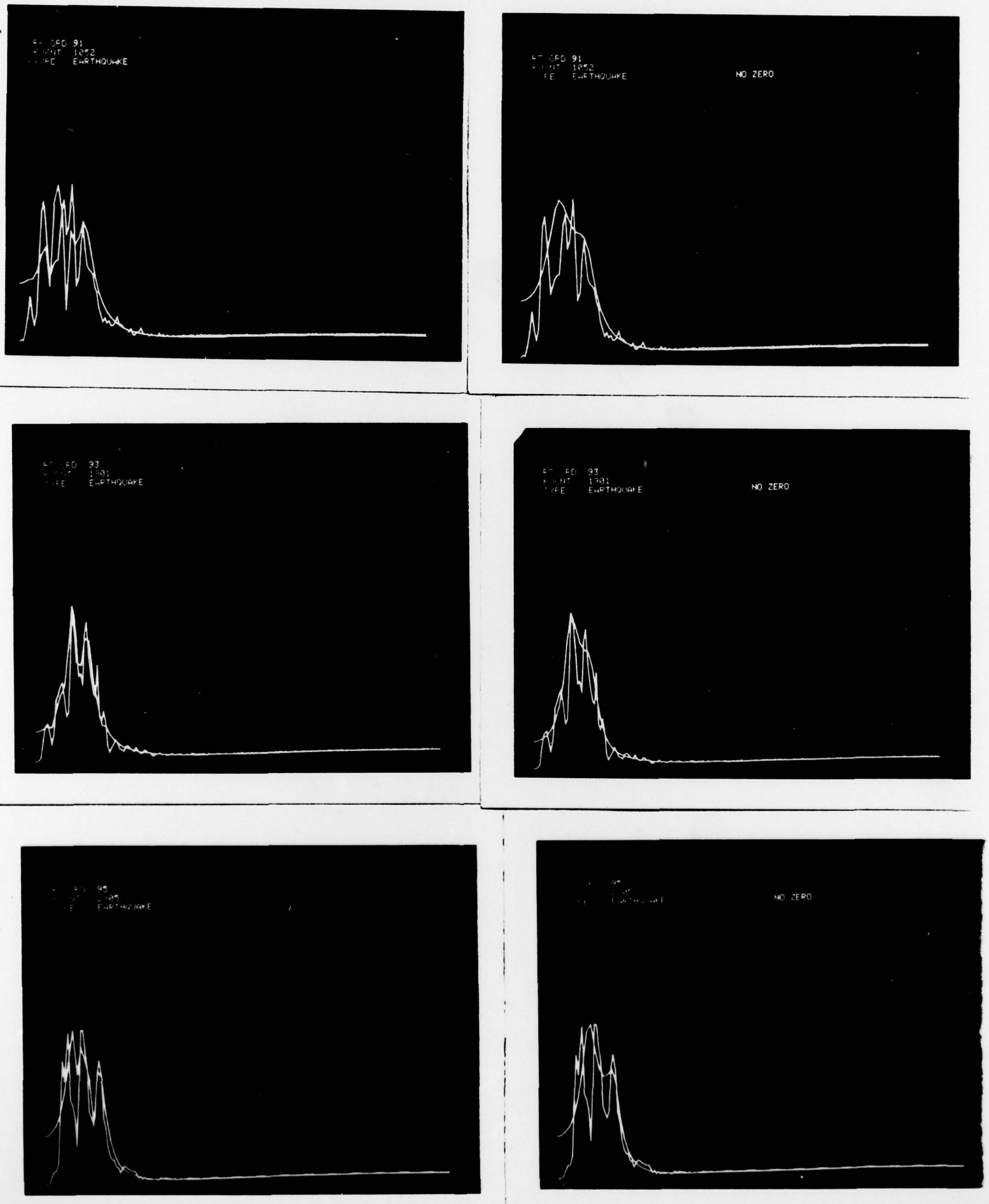
$$y_n = h_n * s_N = \varepsilon_n * b_n * s_n = \varepsilon_n * (b_n * s_n) = \varepsilon_n * \omega_n \quad (5)$$

where $\omega_n = b_n * s_n$ is defined as a composite wavelet consisting of the reverberation wavelet b_n and source pulse s_n. Thus Eq. (5) describes the normal incidence reflection seismogram, where b_n represents the autoregressive component and $s_n * \varepsilon_n$ the moving average component. The basic deconvolution problem is to filter y_n such that we can best recover the reflection coefficient sequence ε_n.

3. Spectral Matching and the ARMA Model

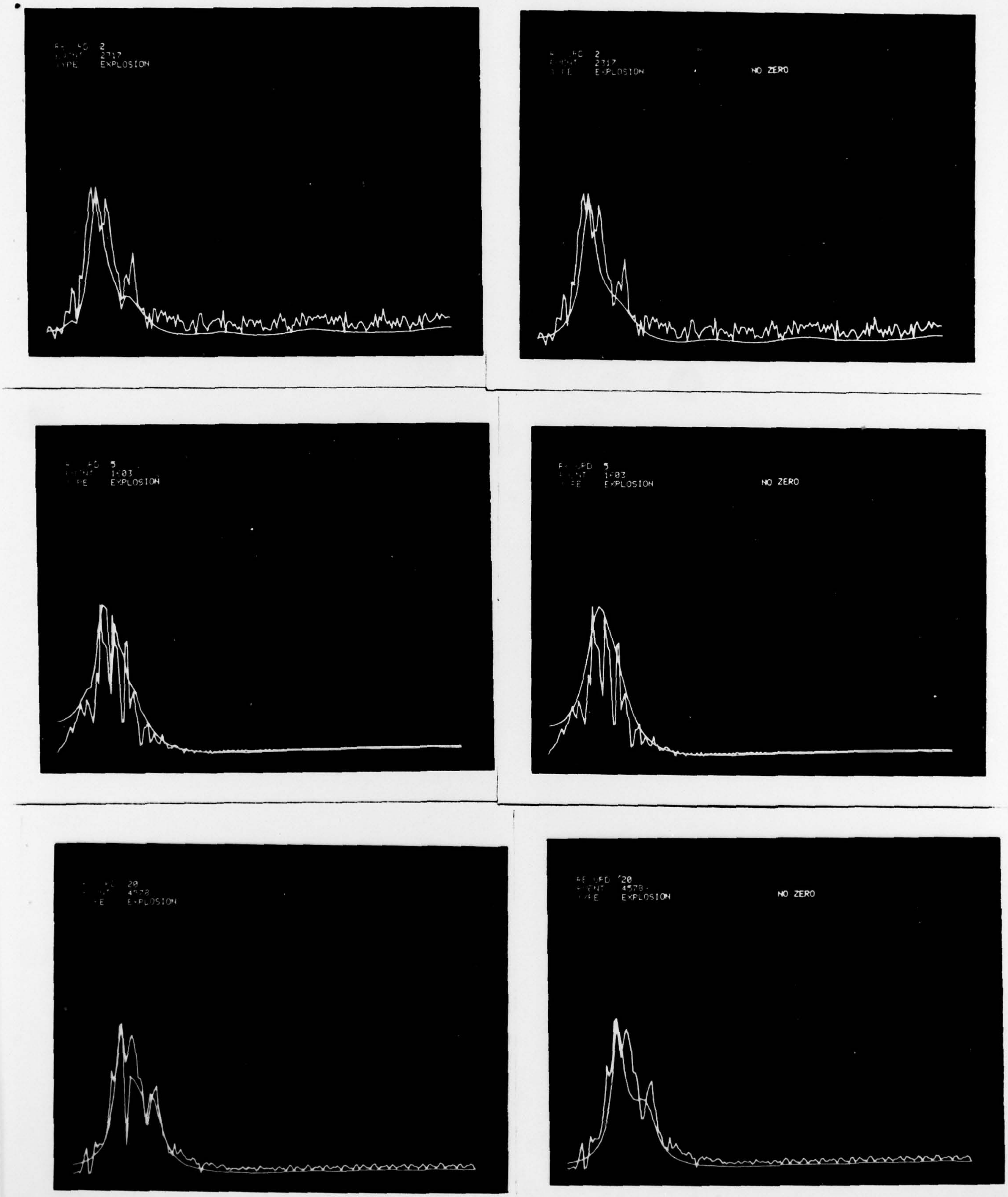
The ARMA model as derived in the previous section is the most general linear seismic signal model. Theoretically speaking, the spectrum of any physical signal can be matched, i.e. fitted, perfectly by an autoregressive model with an arbitrarily high order. For a typical set of teleseismic waveforms, a good spectral matching based on the autoregressive, i.e. all-pole, model has been reported [1][2]. If the ARMA, i.e. pole-zero, model is used, a better spectral matching is expected. The degree of spectral matching can be measured by the mean squared error between the actual and the modelled signals. Figure 4 illustrates spectral matching by pole-zero model which has lower mean squared error. Again the spectral matching is good. However, the problems associated with the ARMA model are quite obvious: (1) The order of the model must be finite in practice. The linear model is limited in its capability not only in spectral matching but also represents only a first order approximation to the original signal. (2) Computationally the order of the model and the coefficients in both numerator and denominator must be determined. This is far from being a simple task. In fact there has not been a satisfactory solution to the problem of determining the numerator polynomial and the order of the model.

Fig. 4



Note Left side photos are for pole-zero model with better fit than all-pole model on right sid

Fig. 4 (continued)



4. Parameter Estimation and Computation

In this section we first consider the all-pole linear prediction analysis We assume that the signal s(n), $0 \leq n \leq N - 1$, can be approximated as a weighted linear summation of past samples, denoted as

$$s_n = - \sum_{k=1}^{p} a_i \, s_{n-i} \qquad (6)$$

where a_i are the predictor coefficients which are the coefficients of the AR model, and p is the order of the filter. The method of least squares is most often used [3] to estimate a_i by minimizing the total mean squared errors where the error is defined as $e_n = s_n - \hat{s}_n$. There are two distinct methods for estimating the parameters. The autocorrelation method minimizes the error e_n over an infinite duration. Since the signal is of finite duration in practice, the infinite duration signal can be windowed to become finite duration. The autocorrelation matrix is a Toepliz matrix whose special properties lead to efficient Levinson and Durbin recursion algorithms for estimating a_i. The second method is covariance method which considers a finite duration signal only so it minimizes the error over a finite interval. The covariance matrix is symmetric but the diagonal terms are not equal. The assumption of zero values for data outside the finite duration is not valid. This is the main source of inaccuracy in both methods. The autocorrelation method guarantees filter (model) stability while the covariance method does not.

Computationally the parameters can be determined without major computational load. The estimation of autocorrelation or covariance from data points may take most of computation time when the number of data points far exceed the order of the filter, as is often the case.

The maximum entropy method states that the least assumptions should be made about the unobserved data points. This may be restated by saying that the spectrum estimated should be maximally random (maximum uncertainty). The maximum entropy solution for parameters should be the same as that of the AR model except for details of the algorithm.

After the parameters of the AR model are determined we shall then use the ARMA model by incorporating the numerator polynomials. Let the denominator be now fixed, we can determine the numerator polynomial, from Eq. (4) by examining the ratic,

$$\frac{B(z)}{H(z)} = \frac{1}{\varepsilon_1 z^{-1} + \varepsilon_2 z^{-2} + \ldots + \varepsilon_N z^{-N}} \tag{7}$$

where the coefficients ε_i can be determined by the methods which are used for the AR model as the inverse z-transform of $B(z)/H(z)$ is now available. Obviously one iteration may not be enough. We can hold ε_i's constant and adjust a_i's by repeating the above procedure. This method is much simpler in computation than direct estimation [3] of the parameters of the ARMA model. We have tested this method on short length artificial data sequence to verify the convergence of the recursive procedure. Convergence is verified experimentally. For real data such as of length 1024 points, it will be difficult, however, to determine the coefficients if the order of the filter is high.

Recently the lattice structures have been developed which offer a convenient visual realization of the Levinson recursion. For applications where the short-term spectrum changes as a function of time, the lattice offers a simple, fast-converging adaptive structure that has given results superior to the traditional adaptive transversal filter [4][5].

In this section we have briefly discussed techniques related to data modeling by least squares, especially the estimation of ARMA model parameters. The application to seismic signal processing is not limited to spectral estimation and data compression. There are good physical interpretation of parameters and related quantities such as the reflection coefficients. The parameters are potentially useful features for classification of teleseismic events. Good spectral estimation leads to accurate computation of spectral ratio which is another useful features in sesimic discrimination. Some recent articles on spectral analysis in seismic data are [6][7].

5. Homomorphic Versus Predictive Deconvolution

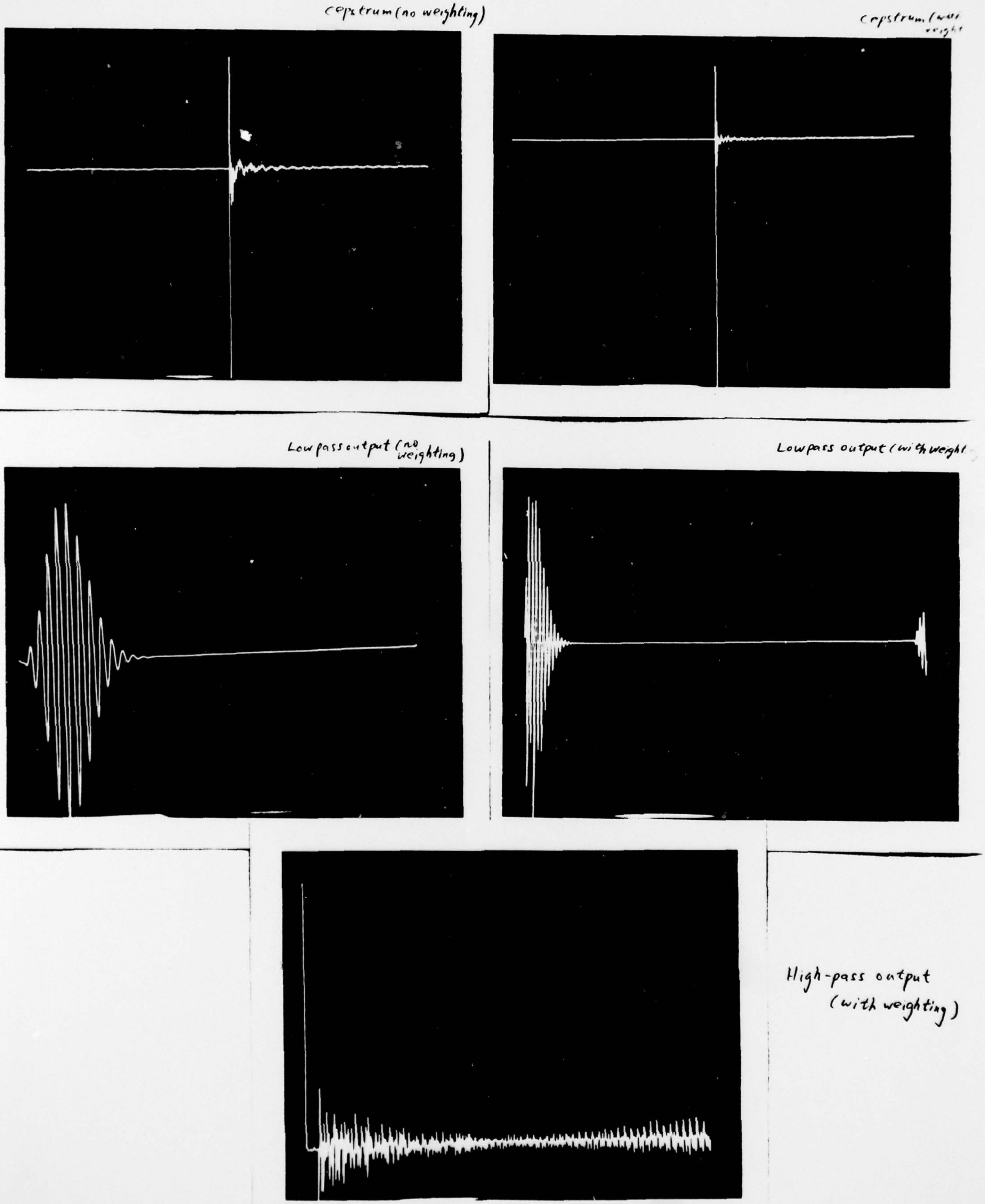
In determining the source pulse by using the deconvolution method, both predictive and homomorphic deconvolution methods have been extensivley studied. They represent two important but quite different approach to the problem. In Eq. (5) the theoretical reverberation wavelet b_n is minimum phase, while the source pulse s_n is not. For given autocorrelation, only the minimum phase pulse corresponsding to s_n can be determined. The problem in predictive deconvolution is thus to determine an all-pass filter to obtain a source pulse with correct phase characteristic. To do so an assumption about the phase characteristic of the source pulse is required. For the homomorphic deconvolution [8][9], the cutoff quefrencies that produce proper pulse estimate actually also requires an assumption about delay (or phase) properties of the source pulse. However, such phase assumption is less critical in homomorphic deconvolution than in predictive deconvolution. In homomorphic deconvolution an exponential weighting of the data sequence is usually necessary to remove computational instability due to the nonminimum phase source pulse. Figure 5 shows some results of cepstral analysis on the teleseismic records.

In the homomorphic deconvolution the reflection coefficient sequence can be determined once the complex cepstrum corresponding to the source pulse and reverberation is removed. For the predictive deconvolution, one assumes that the reflection coefficients are a random uncorrelated sequence to be estimated.

6. Kalman Filtering Approach

The Kalman filtering approach can be used to obtain optimal smoothed estimates of the reflection coefficient sequence from seismic traces with noise [10]. The seismic trace can be interpreted as the sum of additive noise and the output of a linear system, with response ω_n given by Eq. (5), excited by white noise corresponding to the reflection coefficient sequence. So the estimation of reflection coefficient is now the same problem as estimating the random

Fig. 5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(with weighting)

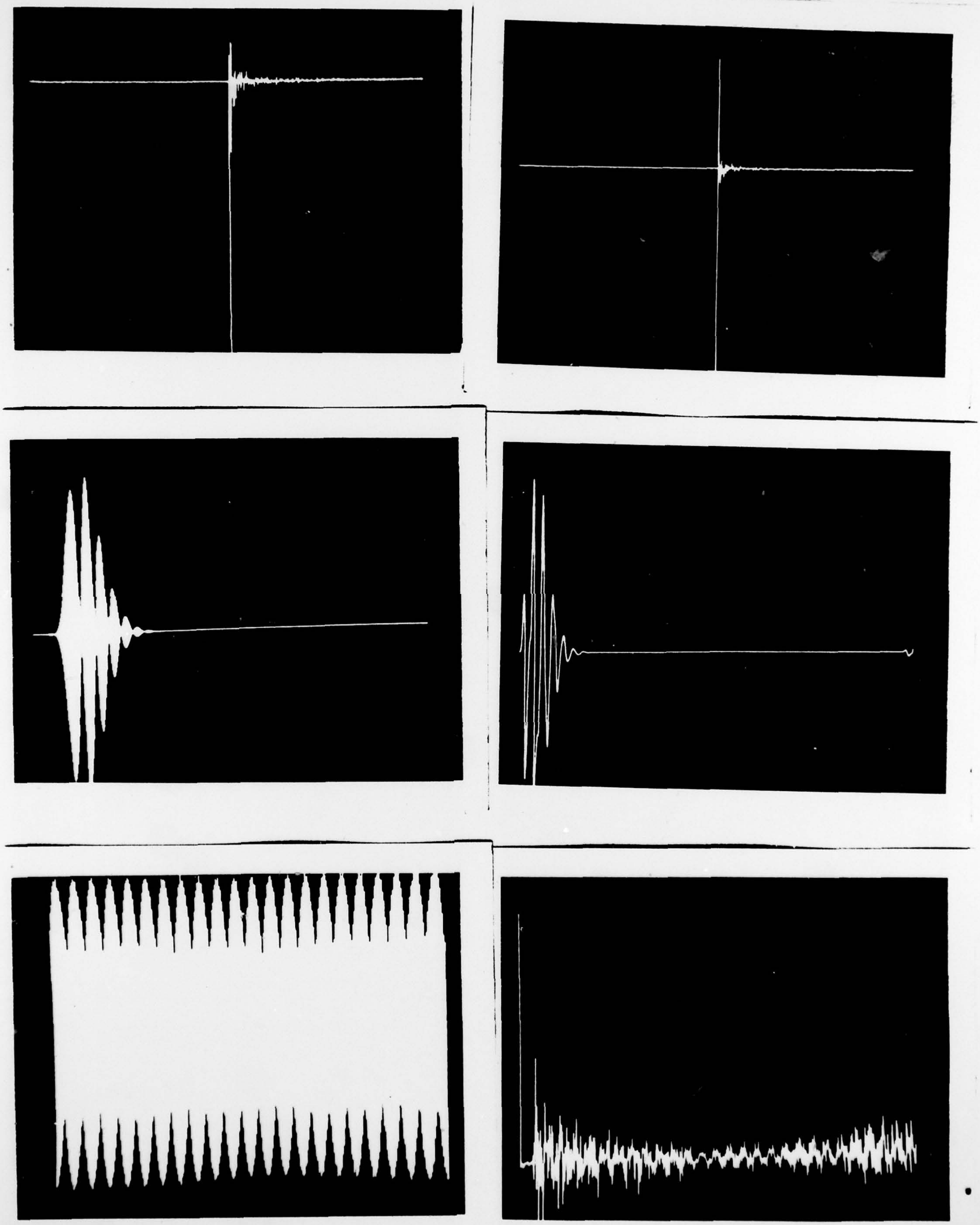

Fig 5 continued

disturbance in a state equation. Assumption is made that basic composite wavelet is known a priori, and that the both additive noise and the white noise for the reflection coefficient sequence have known covariance matrices, either of which may be time varying. The Kalman filtering approach permits a more flexible modeling assumption than the Wiener filtering to the predictive deconvolution.

7. Measuring the First Arrival Time

In microearthquakes and in explosive events, for example, it will be necessary to measure accurately the first arrival time. The ambiguity associated with the measurement of the first arrival time is due to the facts that the signal is contaminated by noise and the wave shape of the first arrival is unknown. Thus the methods of "beam forming" and "matched filtering" are not acceptable. However, the first arrival does occur in a context, the features of which can be determined more reliably. Anderson [11] developed a simple but robust algorithm for automatic analysis of microearthquake data to pick the first arrival with good accuracy. The algorithm uses informations from multiple levels such as a tentative location, detection of the event, arrival time residuals, and the features which represent physical measurements of the seismic wave including the first and second zero crossing, the first maximum in the half cycle, etc. Syntactic pattern recognition should be a useful approach to improve the algorithm.

References

1. C.H. Chen, "Seismic pattern recognition", Geoexploration Journal, Vol. 16, No. 1/2, pp. 133-146, April 1978.

2. C.H. Chen, "On digital signal modelling and classification with the teleseismic data", IEEE International Conference on Acoustics, Speech and Signal Processing Record, Tulsa, OK, April 1978.

3. J. Makhoul, "Linear prediction: a tutorial review", Processings of the IEEE, Vol. 63, No. 4, pp. 561-580, April 1978.

4. J. Makhoul and R. Viswanathan, "Adaptive lattice methods for linear prediction", IEEE International Conference on Acoustics, Speech and Signal Processing Record, Tulsa, OK, April 1978.

5. J. Makhoul, "Lattice methods in speech estimation", Proceedings of the RADC Spectral Estimation Workshop, May 24-26, 1978.

6. T.E. Landers and R.T. Lacoss, "Some geophysical applications of autoregressive spectral estimates", IEEE Trans. on Geoscience Electronics, Vol. GE-15, No. 1, pp. 26-32, January 1977.

7. L.J. Griffiths and R. Prieto-Diaz, "Spectral analysis of natural seismic events using autoregressive techniques", IEEE Trans. on Geoscience Electronics, Vol. GE-15, No. 1, pp. 13-25, January 1977.

8. A.V. Oppenheim and R. Schafer, "Digital Signal Processing", Prentice-Hall Inc., 1975.

9. J.M. Tribolet, "Applications of short-time homomorphic signal analysis to seismic wavelet estimation", Geoexploration Journal, Vol. 16, No. 1/2, pp. 75-96, April 1978.

10. J.M. Mendel, "White-noise estimators for seismic data processing in oil exploration", IEEE Trans. on Automatic Control, Vol. AC-22, No. 5, pp. 694-706, October 1977.

11. K.R. Anderson, "Automatic analysis of microearthquake network data", Geoexploration Journal, Vol. 16, No. 1/2, pp. 159-175, April 1978.

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1. REPORT NUMBER AFOSR-TR- 78-1096	2. GOVT ACCESSION NO.	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle) AN INTRODUCTION TO SEISMIC SIGNAL PROCESSING		5. TYPE OF REPORT & PERIOD COVERED Interim
		6. PERFORMING ORG. REPORT NUMBER TR No. EE-78-3
7. AUTHOR(s) C.H. Chen		8. CONTRACT OR GRANT NUMBER(s) AFOSR 76-2951
9. PERFORMING ORGANIZATION NAME AND ADDRESS Southeastern Massachusetts University Department of Electrical Engineering North Dartmouth, Massachusetts 02747		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS 61102F 2304/A2
11. CONTROLLING OFFICE NAME AND ADDRESS Air Force Office of Scientific Research/NM Bolling AFB, Washington, DC 20332		12. REPORT DATE 8 June 1978
		13. NUMBER OF PAGES 14
14. MONITORING AGENCY NAME & ADDRESS (if different from Controlling Office)		15. SECURITY CLASS. (of this report) UNCLASSIFIED
		15a. DECLASSIFICATION DOWNGRADING SCHEDULE

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

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