

SPECTRAL ANALYSIS OF APERIODIC DIGITAL SIGNALS

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CHAPTER I

INTRODUCTION

This report can essentially be divided into two parts. In the first part, the notion of the time-varying Fourier transform which was introduced recently [1] for noise-free discrete signals is extended to the case when noise is present. This is achieved by introducing some damping in the filtering process associated with the time-varying Fourier transform. The second part presents a study of Arnold's on-line computational algorithm [2].

It is demonstrated that Arnold's algorithm can be used to good advantage prior to classification for signal representation of transient waveforms which are embedded in noise. It is especially useful for those cases in which the signal to noise ratio is low. Examples of such applications include the following [2] :

- (1) The classification of moving traffic in the presence of a noisy background.
- (2) The discrimination between classes of seismic events in a noisy background.
- (3) The classification of both man-made and biologically generated transients in an ocean background.

If the transient waveforms are well above the noise to the extent that their epoch and duration can be easily determined, then the fast Fourier transform (FFT) technique [3] may be used as a means of signal representation prior to classification. However, in applications of the type cited above, the transients are usually well below the level of the noise. Consequently their

epochs and durations are not known. To overcome this, one could choose an upper bound $T_{\max}$ as the duration of any transient of interest and then use the FFT technique. However, this is not satisfactory since the arbitrary segmentation could result in spectral distortion.

Next, it is demonstrated that the time-varying Fourier transform, on being modified as cited above, can be used as an effective tool to estimate the Fourier power and phase spectra of transients in the presence of noise. Again, it is shown that such estimation can be achieved with any desired frequency resolution. In conclusion, it is demonstrated that the spectral estimates so obtained are superior to those obtained by standard smoothing techniques.

The above applications are considered in Chapter IV of this report. In Chapters II and III some fundamental aspects of Arnold's algorithm and the time-varying Fourier transform are presented. Conclusions pertaining to the study undertaken and corresponding recommendations for future work are presented in Chapter V.

CHAPTER II

TIME-VARYING FOURIER TRANSFORM AND RELATED SPECTRA

2.1 Fourier Transform of a Discrete Signal

Let $X(t)$ be a continuous real-valued signal. It can be approximated to a series of rectangular segments of width Δt as shown in Figure 2.1 (a). Now the signal can be represented by the sequence of impulses $X^*(t)$ shown in Figure 2.1(b). The impulse at the point $m\Delta t$ has a strength $\Delta t X(m)$, which is area of a rectangle formed by the base Δt and the height $X(m)$ at $m\Delta t$ in Figure 2.1(a).

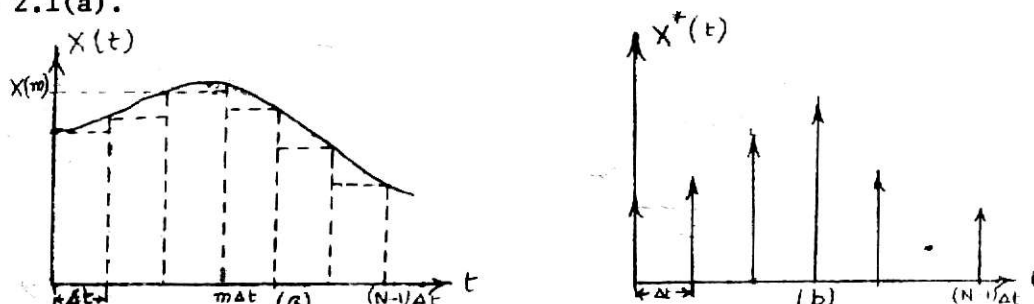


Figure 2.1 Decomposition of Signal into Impulse Train

The discrete signal $X^*(t)$ can be written as*

$$X^*(t) \approx \sum_{m=0}^{N-1} [\Delta t X(m)] \delta(t - m\Delta t) \quad (2-1a)$$

where $\delta(t)$ is the Dirac or impulse function. If $X(t)$ has a bandwidth of B Hz, then from Shannon's Sampling theorem Δt must be less than or equal to $1/2B$ sec.

Fourier transform $F_X^*(\omega)$ of $X^*(t)$ is given by

$$F_X^*(\omega) = \Delta t \int_{-\infty}^{\infty} \sum_{m=0}^{N-1} X(m) \delta(t - m\Delta t) e^{-i\omega t} dt \quad (2-1b)$$

*See for example, "Lin. Network Analysis", by Seshu and Balabanian, John Wiley, 1959, p.205.

Interchanging the order of integration and summation in Eq. (2-1b) we obtain

$$\begin{aligned} F_{x^*}(\omega) &= \Delta t \sum_{m=0}^{N-1} X(m) \int_{-\infty}^{\infty} \delta(t-M\Delta t) e^{-i\omega t} dt \\ &= \Delta t \sum_{m=0}^{N-1} X(m) e^{-im\omega\Delta t} \end{aligned} \quad (2-2)$$

$$= \Delta t \sum_{m=0}^{N-1} X(m) \cos(\omega m \Delta t) - i \sum_{m=0}^{N-1} X(m) \sin(\omega m \Delta t) \quad (2-3)$$

that is,

$$F_{x^*}(\omega) = \Delta t \{ R(\omega) - i I(\omega) \} \quad (2-4)$$

where

$$R(\omega) = \sum_{m=0}^{N-1} X(m) \cos(\omega m \Delta t)$$

and

$$I(\omega) = \sum_{m=0}^{N-1} X(m) \sin(\omega m \Delta t)$$

$F_{x^*}(\omega)$ in Eq. (2-4) is the desired Fourier transform of a given discrete signal $x^*(t)$.

2.2 Time Varying Fourier Transform [1]

$F_{x^*}(\omega)$ in Eq. (2-4) can be expressed in terms of a (2x1) vector to obtain,

$$\underline{F}_{x^*}(\omega) = \Delta t \begin{bmatrix} R(\omega) \\ I(\omega) \end{bmatrix} \quad (2-5)$$

Now, consider the (2x2) matrix

$$[L(\omega)] = \begin{bmatrix} \cos(\omega \Delta t) & -\sin(\omega \Delta t) \\ \sin(\omega \Delta t) & \cos(\omega \Delta t) \end{bmatrix} \quad (2-6)$$

Since $[L(\omega)]$ is orthogonal, it has the property

$$\left[L(\omega) \right]^m = \begin{bmatrix} \cos(m\omega\Delta t) & -\sin(m\omega\Delta t) \\ \sin(m\omega\Delta t) & \cos(m\omega\Delta t) \end{bmatrix} \quad (2-7)$$

Thus, from Eqs. (2-5) and (2-7) it follows that,

$$\underline{F}_{x*}(\omega) = \Delta t \sum_{m=0}^{N-1} \left[L(\omega) \right]^m \underline{b}X(m) \quad (2-8)$$

where

$$\underline{b} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

We introduce the recurrence relation

$$\begin{aligned} \underline{Z}(\omega, k) &= \left[L(\omega) \right] \underline{Z}(\omega, k-1) + \underline{b}X(N-1-k) \\ k &= 0, 1, 2, \dots, (N-1) \end{aligned} \quad (2-9)$$

where k denotes the instant of time $t = k\Delta t$ and

$$\underline{Z}(\omega, -1) = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

With $k=0$, and $k=1$, Eq. (2-9) yields

$$\underline{Z}(\omega, 0) = \left[L(\omega) \right] \underline{Z}(\omega, -1) + \underline{b}X(N-1) \quad (2-10)$$

and

$$\begin{aligned} \underline{Z}(\omega, 1) &= \left[L(\omega) \right] \underline{Z}(\omega, 0) + \underline{b}X(N-2) \\ &= \left[L(\omega) \right] \left\{ \left[L(\omega) \right] \underline{Z}(\omega, -1) + \underline{b}X(N-1) \right\} + \underline{b}X(N-2) \\ &= \left[L(\omega) \right]^2 \underline{Z}(\omega, -1) + \left[L(\omega) \right] \underline{b}X(N-1) + \underline{b}X(N-2) \end{aligned} \quad (2-11)$$

Proceeding on similar lines we arrive at the fundamental relationship

$$\underline{Z}(\omega, N-1) = \sum_{m=0}^{N-1} \left[L(\omega) \right]^m \underline{b}X(m) = \frac{1}{\Delta t} \underline{F}_{x*}(\omega) \quad (2-12)$$

where $\underline{F}_{x*}(\omega)$ is the (2×1) vector defined in Eq. (2-5). Eq. (2-12) states that, at the instant $k=(N-1)$, $\underline{Z}(\omega, k)$ in Eq. (2-9) yields the conventional Fourier transform defined in Eq. (2-4). $\underline{Z}(\omega, k)$ can therefore be defined as

the time-varying Fourier transform. Again if we denote

$$\underline{Z}(\omega, k) = \begin{bmatrix} Z_1(\omega, k) \\ Z_2(\omega, k) \end{bmatrix} \quad (2-13)$$

then the time-varying power and phase spectra can be defined as

$$P(\omega, k) = (\Delta t)^2 \left| \underline{Z}(\omega, k) \right|^2 \quad (2-14a)$$

$$\text{and } \Psi(\omega, k) = \tan^{-1} \left\{ \frac{Z_2(\omega, k)}{Z_1(\omega, k)} \right\} \quad (2-14b)$$

respectively. Eq. (2-9) yields an efficient recursive algorithm to compute the time-varying power and phase spectra. This is illustrated in Figure 2.2 for the case of computing the time-varying power spectrum at a set of points $\omega = \omega_n, n=1, 2, \dots, M$. From Figure 2.2 it follows that the computational process can be associated with a bank of filters characterized by the (2x2) matrices $\underline{L}(\omega_n), n=1, 2, \dots, M$.

2.3 Noise Considerations [2]

In the above analysis it is assumed that the signal $X^*(t)$ is noise-free. In many real-world problems, however, one does not have isolated processes, but usually a combination, such as periodic and transient signals in a noisy background. In such cases, the spectra discussed in the previous section need smoothing if they are to yield consistent estimates. The recurrence relation in Eq. (2-9) can be extended to handle the noisy signals with some modifications. This is discussed in what follows.

The desired frequency range is covered by a bank of constant Q filters whose frequencies are equally spaced on a logarithmic scale. The matrix considered in the Eq. (2-6) is redefined for the n -th filter in the filter bank as,

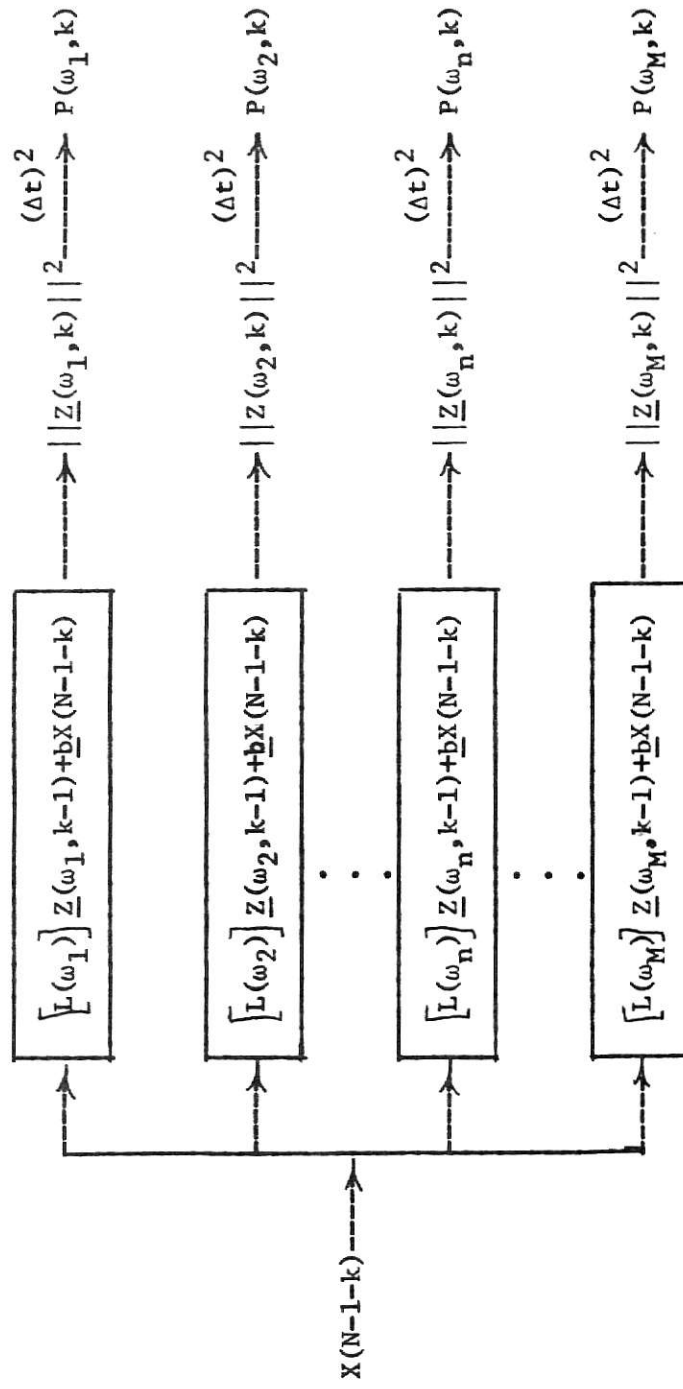


Figure 2.2 Computation of the Time-Varying Power Spectrum

$$\left[L(\omega_n) \right] = \begin{bmatrix} e^{-\alpha \Delta t} \cos(\omega_o \Delta t) & -e^{-\alpha \Delta t} \sin(\omega_o \Delta t) \\ e^{-\alpha \Delta t} \sin(\omega_o \Delta t) & e^{-\alpha \Delta t} \cos(\omega_o \Delta t) \end{bmatrix} \quad (2-15)$$

where $\alpha = \zeta \omega_n$, ζ is called the damping factor

$$\text{and } \omega_o = \omega_n \sqrt{1 - \zeta^2} \quad (2-16)$$

Then, corresponding to Eq. (2-9) we obtain

$$\begin{aligned} \underline{Z}(\omega_n, k) &= \left[L(\omega_n) \right] \underline{Z}(\omega_n, k-1) + \underline{b} X(N-1-k) \\ k &= 0, 1, 2, \dots, N-1 \end{aligned} \quad (2-17)$$

Again, the time varying power and phase spectra are respectively given by

$$P(\omega_n, k) = (\Delta t)^2 \left| \underline{Z}(\omega_n, k) \right|^2 \quad (2-18a)$$

and

$$\Psi(\omega_n, k) = \tan^{-1} \left\{ \frac{Z_2(\omega_n, k)}{Z_1(\omega_n, k)} \right\} \quad (2-18b)$$

The computational process is identical to that shown in Figure 2.2 except that each $\left[L(\omega_n) \right]$ defined in Eq. (2-9) is replaced by that defined in Eq. (2-15). The introduction of the damping has the effect of smoothing the spectrum as each filter has finite bandwidth Δf given by the relation

$$Q = \frac{\omega}{\Delta \omega} = \frac{f}{\Delta f} = \frac{1}{2\zeta} \quad (2-19)$$

The various contiguous filters overlap at their -3dB points as shown in Figure 2.3. For a given Q or equivalently for a given damping factor ζ , the set of center frequencies for the filter bank are readily derived using the algorithm [2],

$$\begin{aligned} f_1 &= (1 + \zeta) f_{\text{base}} \\ f_{n+1} &= \frac{1 + \zeta}{1 - \zeta} f_n, \quad n = 1, 2, \dots, M \end{aligned} \quad (2-20)$$

The frequency points generated by Eq. (2-20) are equally spaced on a logarithmic scale as shown in Figure 2.3.

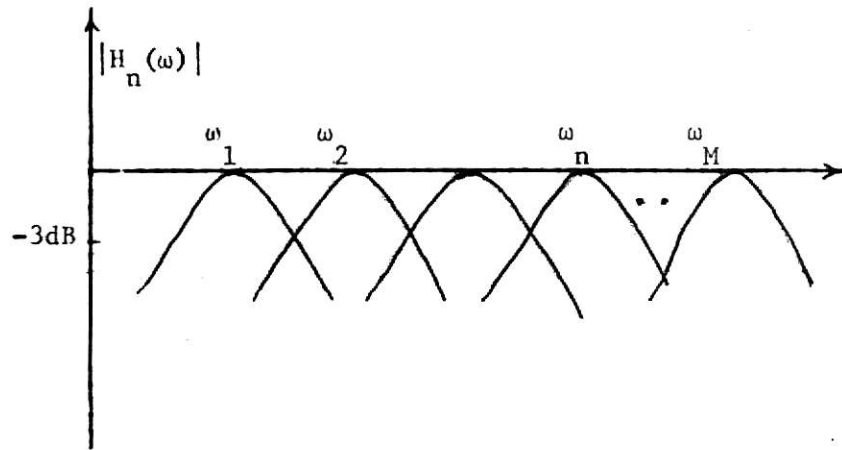


Figure 2.3 Transfer Grain Characteristics of Filter Bank

The base frequency f_{base} is obtained as

$$f_{\text{base}} = f_{\text{NY}} / 10^{\text{DEC}} \quad (2-21)$$

where f_{NY} is the Nyquist or folding frequency given by

$$f_{\text{NY}} = 1/2\Delta t \quad (2-22)$$

and DEC is the desired frequency range in decades.

If damping is not considered, then $\zeta=0$, and hence one considers the bank of filters as having **zero bandwidth at a set of chosen frequencies.**

The corresponding matrix associated with the n -th filter is given by

$$\begin{bmatrix} L(\omega_n) \end{bmatrix} = \begin{bmatrix} \cos(\omega_n \Delta t) & -\sin(\omega_n \Delta t) \\ \sin(\omega_n \Delta t) & \cos(\omega_n \Delta t) \end{bmatrix} \quad (2-23)$$

Clearly, $\begin{bmatrix} L(\omega_n) \end{bmatrix}$ in Eq. (2-23) is the same as $\begin{bmatrix} L(\omega) \end{bmatrix}$ in Eq. (2-6).

2.4 Arnold's Recursive Algorithm [2]

Arnold's recursive algorithm is very similar to Eqs. (2-9) and (2-17). Specifically it is defined as

$$\begin{aligned} \hat{\underline{Z}}(\omega_n, k) &= [\underline{L}(\omega_n)] \hat{\underline{Z}}(\omega_n, k-1) + \underline{b}X(k) \\ k &= 0, 1, \dots, N-1 \end{aligned} \quad (2-24)$$

where $[\underline{L}(\omega_n)]$ is given by Eqs. (2-15) and (2-23) for the damped (i.e. noisy) and undamped (i.e. noise free) cases respectively. Comparing Eq. (2-24) with Eq. (2-9) or Eq. (2-17) it is clear that while the recurrence relation in Eq. (2-24) enables an on-line computation of $||\hat{\underline{Z}}(\omega_n, k)||^2$ (see Figure 2.4), $||\hat{\underline{Z}}(\omega_n, k)||^2 \neq ||\underline{Z}(\omega_n, k)||^2$ where $\underline{Z}(\omega_n, k)$ is defined in (2-13). At best, it can be shown that $||\hat{\underline{Z}}(\omega_n, N-1)||^2 = ||\underline{Z}(\omega_n, N-1)||^2$, for the undamped case. Thus the quantity $||\hat{\underline{Z}}(\omega_n, k)||^2$ can be thought of a sort of instantaneous power of the n-th filter of the filter bank. However Arnold's algorithm has been successfully used in applications such as earthquake detection, where some sort of on-line spectral estimation is preferred. This is because the epoch of a transient caused by the occurrence of a certain event is unknown in such problems.

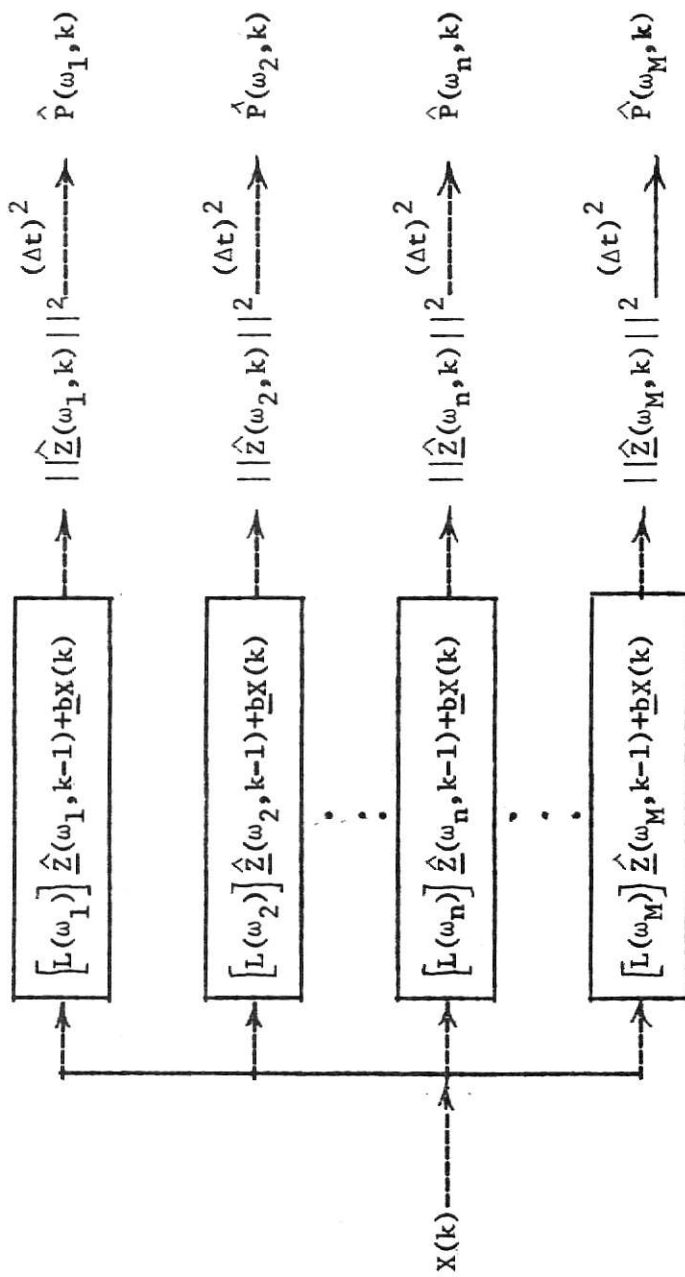


Figure 2.4 Illustration of Arnold's Algorithm

CHAPTER III

RELATIONSHIP BETWEEN A CLASS OF SPECTRA

3.1 Relation Between the Time-Varying and Discrete Fourier Spectra

If $\{X(m)\}$ denotes a sequence $X(m), m=0,1,\dots,N-1$ of N finite, real-valued numbers, then its discrete [3] Fourier transform is defined as

$$C_X(k) = \frac{1}{N} \sum_{m=0}^{N-1} X(m) W^{km}, k = 0,1,\dots,N-1 \quad (3-1)$$

where $W = e^{-i2\pi/N}$

Eq. (3-1) can be rewritten as

$$C_X(k) = \frac{1}{N} \left\{ \sum_{m=0}^{N-1} X(m) \cos\left(\frac{2\pi km}{N}\right) - i \sum_{m=0}^{N-1} X(m) \sin\left(\frac{2\pi km}{N}\right) \right\} \\ k=0,1,\dots,(N-1) \quad (3-2)$$

For the real-valued data sequence $\{X(m)\}$ the DFT power spectrum is defined as

$$|C_X(k)|^2, k = 0,1,\dots,N/2 \quad (3-3)$$

From Eq. (3-2) it follows that,

$$|C_X(k)|^2 = \frac{1}{N^2} \left[\left| \sum_{m=0}^{N-1} X(m) \cos\left(\frac{2\pi km}{N}\right) \right|^2 + \left| \sum_{m=0}^{N-1} X(m) \sin\left(\frac{2\pi km}{N}\right) \right|^2 \right] \\ k=0,1,\dots,N/2 \quad (3-4)$$

represents the DFT power spectrum

Now from Eqs. (2-8) and (2-12) we have

$$\underline{F}_{X^*}(\omega) = (\Delta t) \underline{Z}(\omega, N-1) = (\Delta t) \sum_{m=0}^{N-1} \left[L(\omega)^j \right]^m \underline{b} X(m) \quad (3-5)$$

where,

$$\begin{bmatrix} L(\omega) \end{bmatrix}^m = \begin{bmatrix} \cos(m\omega\Delta t) & -\sin(m\omega\Delta t) \\ \sin(m\omega\Delta t) & \cos(m\omega\Delta t) \end{bmatrix} \quad (3-6)$$

and $\underline{b} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$

In particular, we consider the following set of values taken by ω in Eq. (3-5)

$$\omega_n = \frac{2\pi n}{N\Delta t}, \quad n=0,1,\dots,N/2 \quad (3-7)$$

Then the total power at the frequency ω_n is given by Eq. (2-14) as

$$P(\omega_n, N-1) = (\Delta t)^2 \left| \underline{Z}(\omega_n, N-1) \right|^2 \quad (3-8)$$

where

$$\underline{Z}(\omega_n, N-1) = \begin{bmatrix} \sum_{m=0}^{N-1} X(m) \cos(m\omega_n \Delta t) \\ \sum_{m=0}^{N-1} X(m) \sin(m\omega_n \Delta t) \end{bmatrix} \quad (3-9)$$

Substituting Eq. (3-7) in Eqs. (3-8) and (3-9), the power spectrum can be written as

$$P(\omega_n, N-1) = (\Delta t)^2 \left\{ \left| \sum_{m=0}^{N-1} X(m) \cos\left(\frac{2\pi mn}{N}\right) \right|^2 + \left| \sum_{m=0}^{N-1} X(m) \sin\left(\frac{2\pi mn}{N}\right) \right|^2 \right\} \quad (3-10)$$

$n=0,1,\dots,N/2$

which is the same as the DFT power spectrum defined in Eq. (3-4), except for the scale factor $\left(\frac{1}{N\Delta t}\right)^2$. Thus we conclude that the DFT power spectrum is obtained as a special case of the time-varying power spectrum. Similarly, it can be shown that the DFT phase spectrum can also be obtained as a special case of the time-varying phase spectrum.

3.2 Time-Varying BIFORE Transform Power Spectrum [4]

The BIFORE (Binary Fourier Representation) transform* power spectrum is related to DFT power spectrum as follows [3]

$$\begin{aligned}
 P(0) &= |C_X(0)|^2 \\
 P(S) &= \sum_{k=2^{S-1}}^{2^S-1} |C_X(\langle k \rangle)|^2 \\
 S &= 1, 2, \dots, n; \quad n = \log_2 N
 \end{aligned} \tag{3-11}$$

where $\langle k \rangle$ denotes the decimal number corresponding to the bit reversal of k_{binary} . For example if $k=6$, $k_{\text{binary}}=110$ and hence $\langle k \rangle=3$.

From the preceding section it follows that

$$|C_X(k)|^2 = \frac{1}{N^2} ||Z(\omega_k, N-1)||^2 \tag{3-12}$$

Comparing (3-11) and (3-12) it follows that the time-varying BIFORE transform power spectrum can be defined as

$$\begin{aligned}
 P_B(0, m) &= \frac{1}{(m+1)^2} ||\underline{Z}(\omega_0, m)||^2 \\
 P_B(S, m) &= \frac{1}{(m+1)^2} \sum_{k=2^{S-1}}^{2^S-1} ||\underline{Z}(\omega_{\langle k \rangle}, m)||^2 \\
 \text{for } S &= 1, 2, \dots, n, \quad n = \log_2 N, \quad m = 0, 1, 2, \dots, (N-1)
 \end{aligned} \tag{3-13}$$

It follows that by combining groups of the $||\underline{Z}(\omega_{\langle k \rangle}, m)||^2$ terms given by Eq. (3-13), the BIFORE transform time-varying power spectrum can be computed as shown in Figure 3.1 for the Case $N=8$.

*Also known as the Walsh-Hadamard transform.

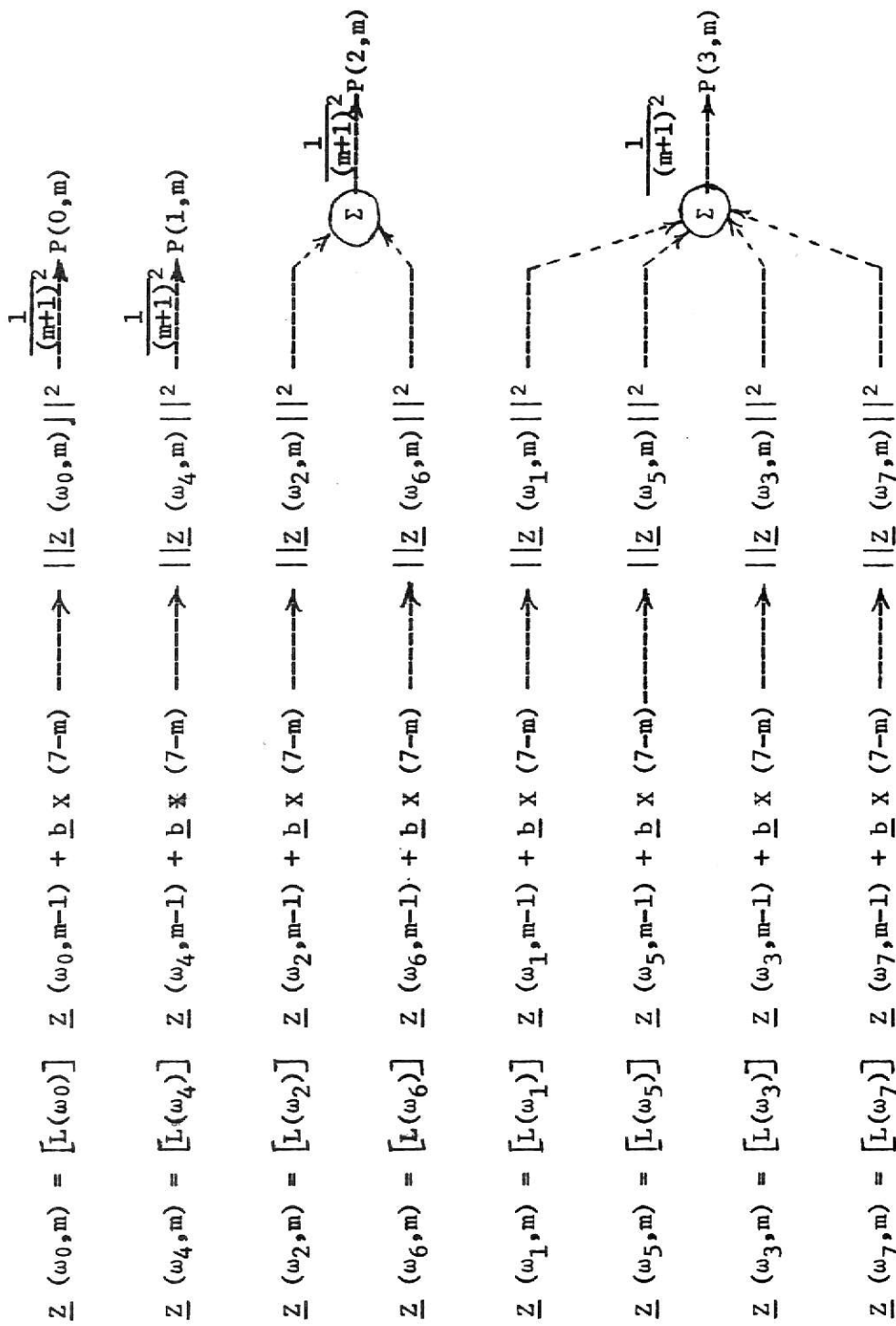


Figure 3.1 Computation of Time-Varying BIFORE Transform Power Spectrum

CHAPTER IV

APPLICATION CONSIDERATIONS

4.1 Introductory Remarks

Two applications pertaining to the recurrence relations defined in Eqs. (2-17) and (2-24) are considered in this chapter. First, it is demonstrated that Arnold's algorithm defined in Eq. (2-24) can be used to secure on-line signal representation (i.e. feature extraction) in pattern recognition problems. On-line signal representation is desirable in cases where the epochs of transients embedded in noise are not known. Such situations are encountered in the processing of seismic and sonar signals [2]. Second, it is demonstrated that damping associated with the recurrence relation in Eq. (2-17) can be used for the spectral estimation of transients embedded in noise whose statistics may be known or unknown.

4.2 On-Line Signal Representation

An experiment is simulated to classify two classes of signals, A and B. The discrete signals belonging to class A and class B are **represented by the waveforms** in Figure 4.1 and Figure 4.2 respectively. In Figures 4.1 and 4.2, A_j and B_j denote the j -th sample of A and B respectively. The discrete values, 50 for each sample of A, are normally distributed random variables with zero mean and unit standard deviation, which are generated using two scientific subroutines, SUBROUTINE GAUSS and SUBROUTINE RANDU.

The discrete values for each sample of B are obtained by adding the discrete data given by

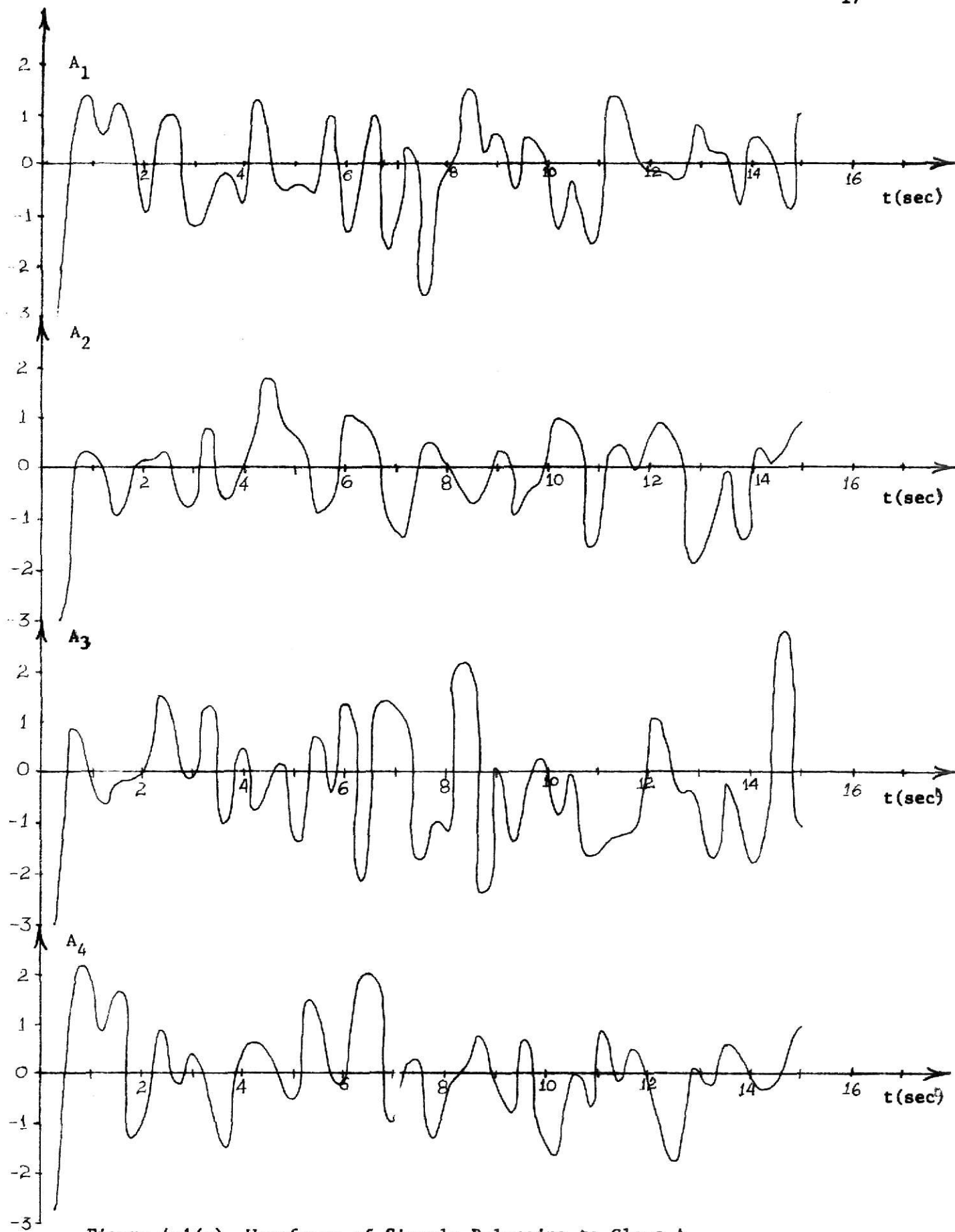


Figure 4-1(a) Waveforms of Signals Belonging to Class A

$$\text{Time scale factor} = \left(\frac{50}{26 \times 15} \right)$$

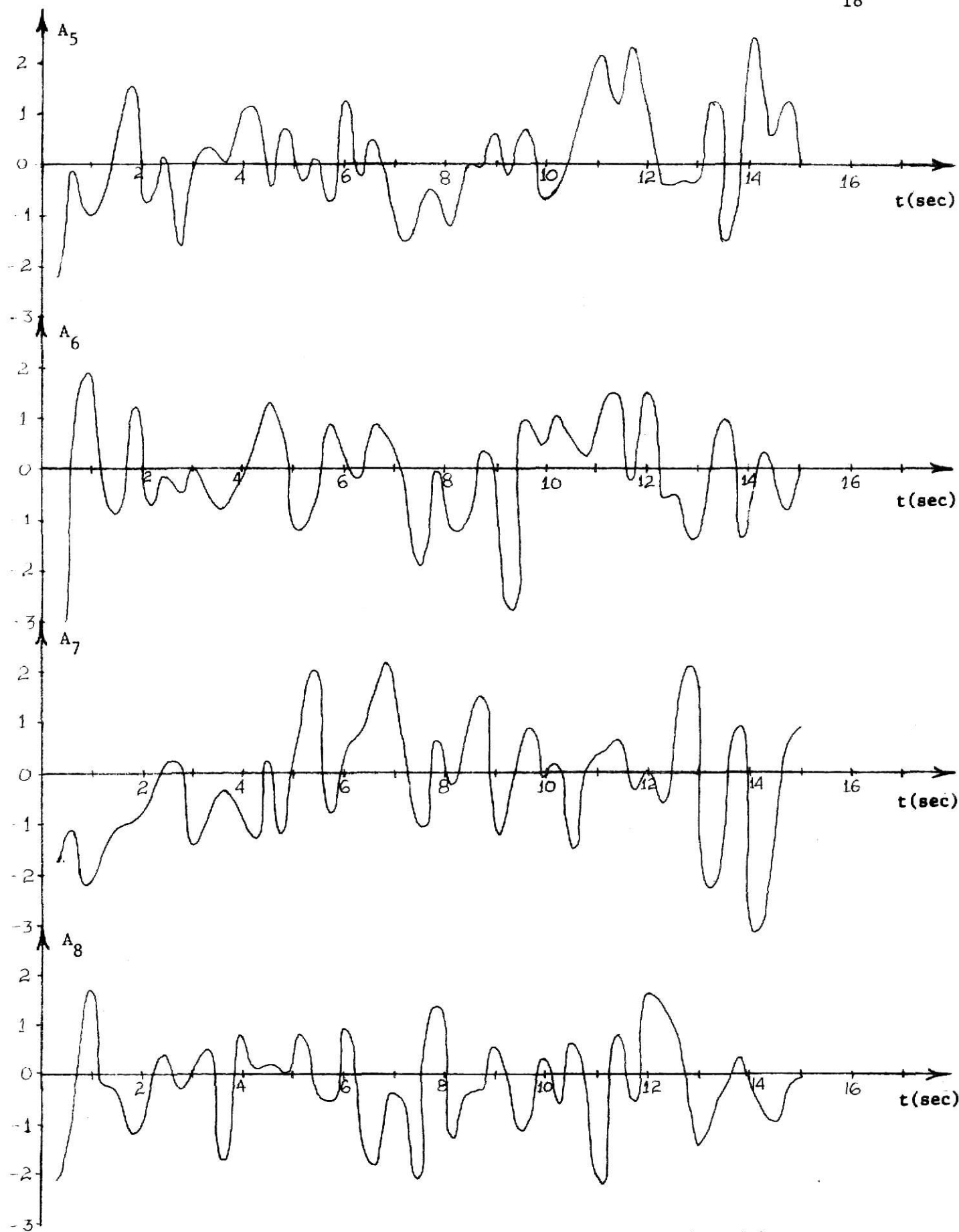


Figure 4-1(b) Waveforms of Signals Belonging to Class A (contd.)

$$\text{Time scale factor} = \left(\frac{50}{26 \times 15} \right)$$

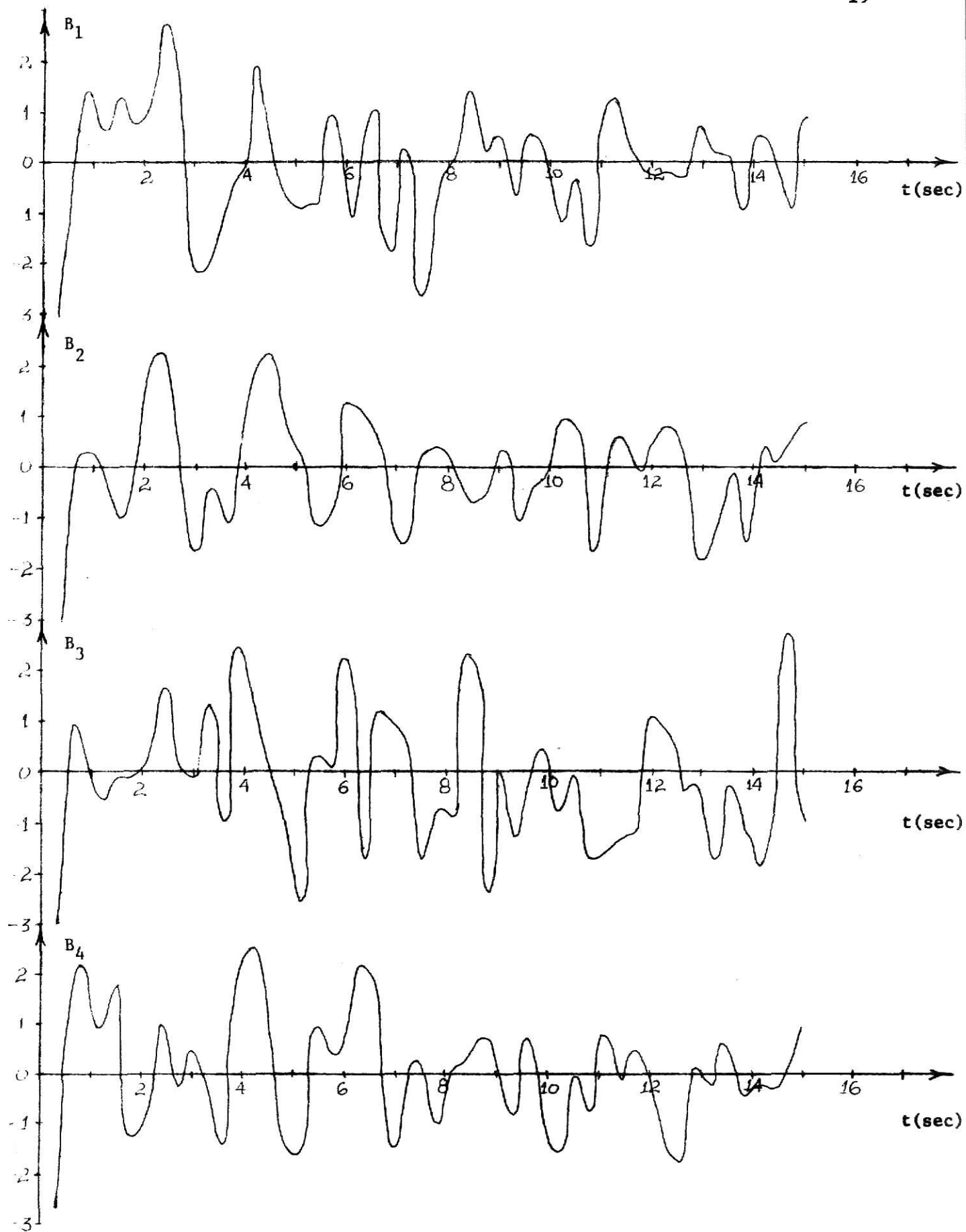


Figure 4.2(a) Waveforms of Signals Belonging to Class B

Time scale factor = (50)

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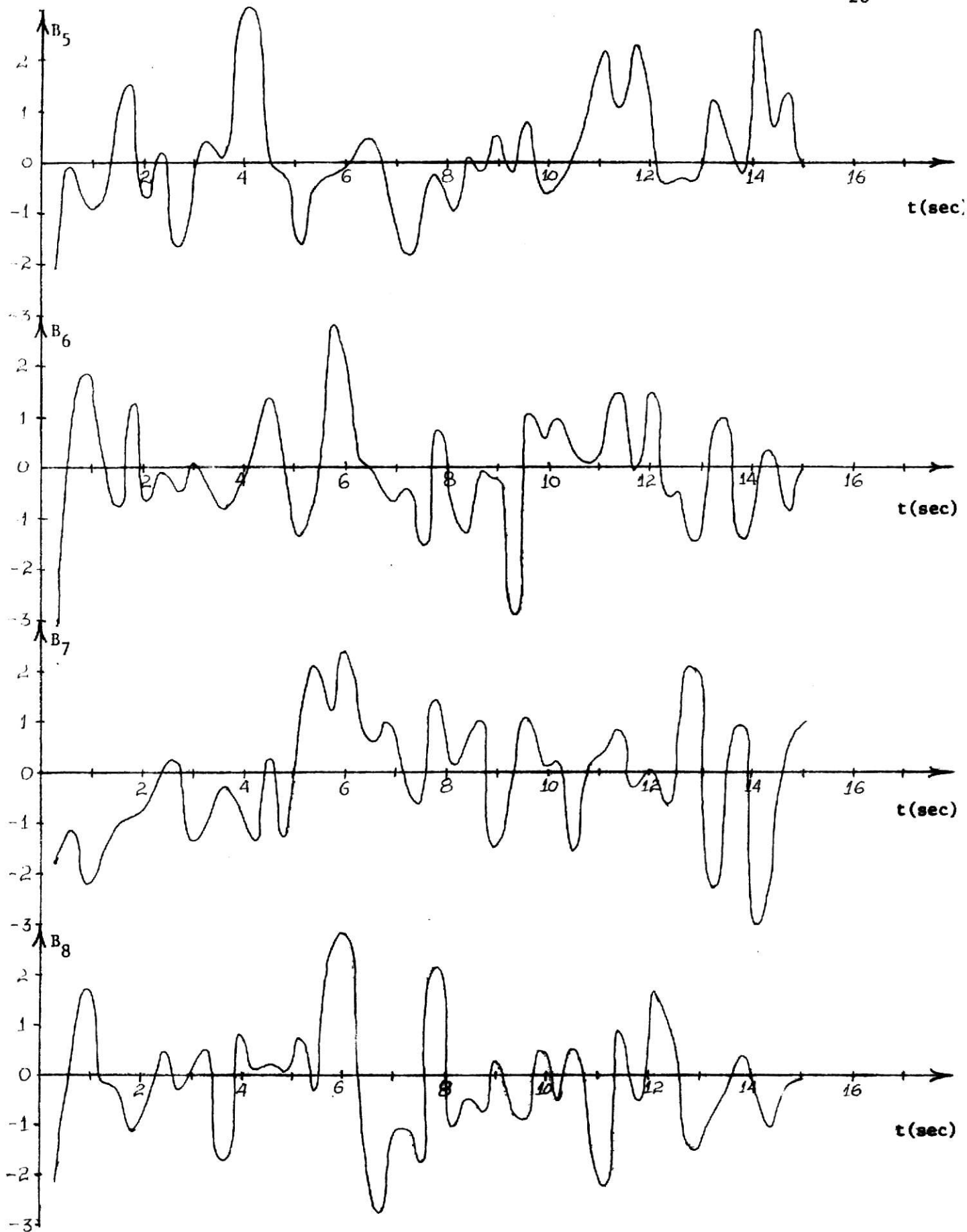


Figure 4.2(b) Waveforms of Signals Belonging to Class B (contd.)

Time scale factor = (50)

$$f(m) = 2.8 \times e^{-m/6} \sin \left(2\pi \times 4 \times \frac{m}{26} \right) \quad m=1,2,\dots,26 \quad (4-1)$$

to the discrete values of each **sample** of A in various positions. The signal-to-noise ratio for the class B was not evaluated. However, the scale factor 2.8 associated with $f(m)$ in Eq. (4-1) was chosen such that the mean-square value of the signal $f(m)$ is approximately one-half times that of the samples of A. That is,

$$\frac{1}{26\Delta t} \sum_{m=1}^{26} f^2(m) \approx \frac{0.5}{8} \left\{ \frac{1}{50\Delta t} \sum_{j=1}^8 \sum_{m=1}^{50} A_j^2(m) \right\} \quad (4-2)$$

where $\Delta t = \frac{1}{26}$ sec.

The corresponding Nyquist frequency is given by $0.5/\Delta t = 13\text{Hz}$ from Eq. (2-22)

A computer program* which implements Arnold's algorithm given in Eq. (2-24) was used to compute the instantaneous spectra of the discrete signals of A and B over a frequency range of 1 decade. Since the Nyquist frequency is 13 Hz, the base frequency is given by $13/10 = 1.3$ Hz from Eq. (2-21). The damping factor ζ was chosen as 0.0588. Substituting this value of ζ in Eq. (2-20) there results 20 filters equally spaced on logarithmic scale between 1.3 Hz and 13 Hz. The center frequencies associated with these 20 filters are listed in Table(4-1).

The corresponding instantaneous power points at the filters having center frequencies 3.97, 4.47 and 5.03 Hz were used as the training sets of the two classes A and B for a training algorithm which uses a least-square mapping technique [3]. The basic idea used is to map (in the least-squares sense) the training samples of a class k , $k=1,2,\dots, K$ into a unit vector

*For a listing of the program, see Appendix I.

TABLE 4-1

Filter #	Center Frequency Hz
1	1.38
2	1.55
3	1.74
4	1.96
5	2.20
6	2.48
7	2.79
8	3.14
9	3.53
10	3.97
11	4.47
12	5.03
13	5.65
14	6.36
15	7.15
16	8.05
17	9.05
18	10.19
19	11.46
20	12.89

V_k in a K -dimensional decision space. All the components of V_k are zero except for the K -th one, which is unity. The corresponding mapping matrix is obtained during the training process. Then the trained classifier assigns an incoming pattern to class i_0 if the pattern is mapped closest to the unit vector V_{i_0} in the decision space. The training vectors used are listed in the Table (4-2).

The resulting "confusion matrix" obtained from the classification of the training sets using the above training algorithm (see Appendix II) is as follows:

$$F = \begin{bmatrix} 8 & 0 \\ 1 & 7 \end{bmatrix}$$

From the matrix F it can be observed that one member of class B is classified as belonging to class A. That is, only one error was incurred in 16 decisions. Thus the above simulated experiment demonstrates the manner in which Arnold's algorithm (see Eq. (2-24)) can be used as an effective tool to secure on-line signal representation in pattern recognition problems.

4.3 Spectral Estimation of Transients

This section demonstrates the smoothing effect of using damped filters characterized by the $[L(\omega_n)]$ matrices defined in Eq. (2-15). A discrete signal was generated as follows:

$$S(m) = 3.97 \times e^{-m/6} \sin \left(2\pi \times 4 \times \frac{m}{26} \right) \quad (4-3)$$

$m=1,2,\dots,26$

Figure 4.3 shows the waveform corresponding to this discrete signal. This signal was then perturbed by additive noise which consists of 26 normally distributed random variables with zero mean and unit variance. An ensemble of 8 samples of perturbed signal was generated, the waveforms corresponding to which are shown in Figure 4.4. We denote the j -th member $j=1,2,\dots,8$, of

TABLE 4-2

Class	Sample #	Instantaneous Power P_i at the i^{th} Instant							
		Filter #10, 3.97 Hz			Filter #11, 4.47 Hz			Filter #12, 5.03 Hz	
		P_{20}	P_{30}	P_{40}	P_{20}	P_{30}	P_{40}	P_{20}	P_{30}
Class A	1	0.6	12.9	0.9	3.6	6.7	12.6	14.8	6.0
	2	7.3	3.8	11.1	17.0	18.9	11.0	7.5	10.3
	3	0.8	4.3	15.2	5.6	4.4	20.2	3.5	15.0
	4	5.7	13.0	4.8	7.5	4.9	3.0	15.3	2.6
	5	6.3	0.2	7.2	0.0	0.6	1.9	2.6	0.9
	6	2.6	7.7	3.5	17.6	0.6	8.0	14.8	3.6
	7	3.0	9.1	0.6	4.2	18.9	1.7	4.2	22.0
	8	4.3	1.5	8.3	9.9	3.4	8.8	3.8	5.4
Class B	1	16.4	31.0	2.8	28.4	4.5	16.7	37.6	9.9
	2	39.4	25.0	26.0	35.2	35.4	11.0	8.5	13.7
	3	35.3	7.5	30.4	46.3	1.8	9.1	32.5	10.5
	4	8.8	17.0	0.3	42.7	13.6	10.8	59.4	7.1
	5	51.5	18.8	12.7	20.6	5.5	7.9	13.9	3.6
	6	9.1	5.1	14.4	39.3	19.8	11.1	47.3	14.4
	7	18.6	11.2	7.9	12.2	2.0	7.3	7.6	4.1
	8	2.6	20.3	30.0	23.1	35.8	4.4	25.0	21.8

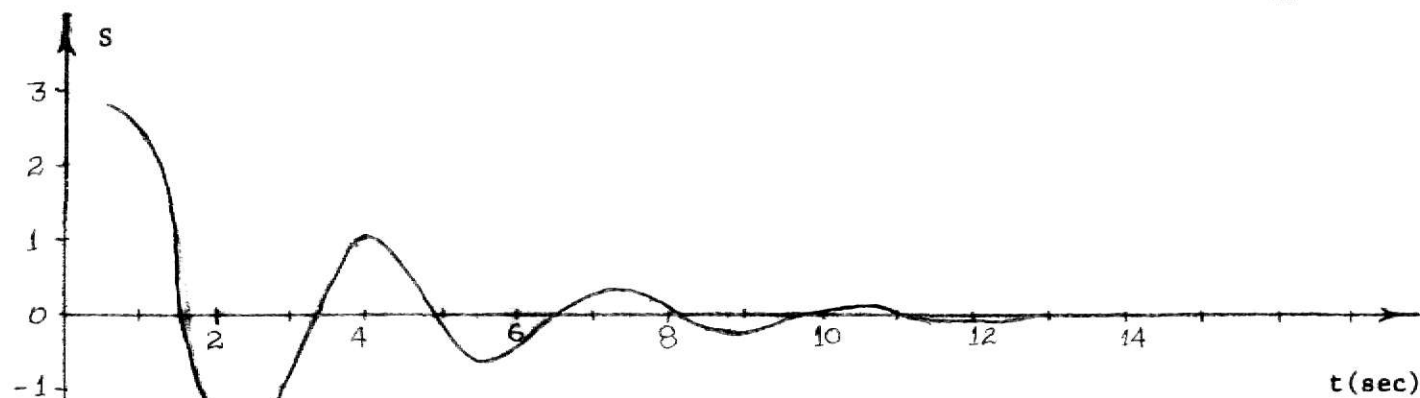


Figure 4-3 Waveform of the signal $S(m)$ Defined in Eq. (4-3)

Time scale factor = $(\frac{1}{13})$

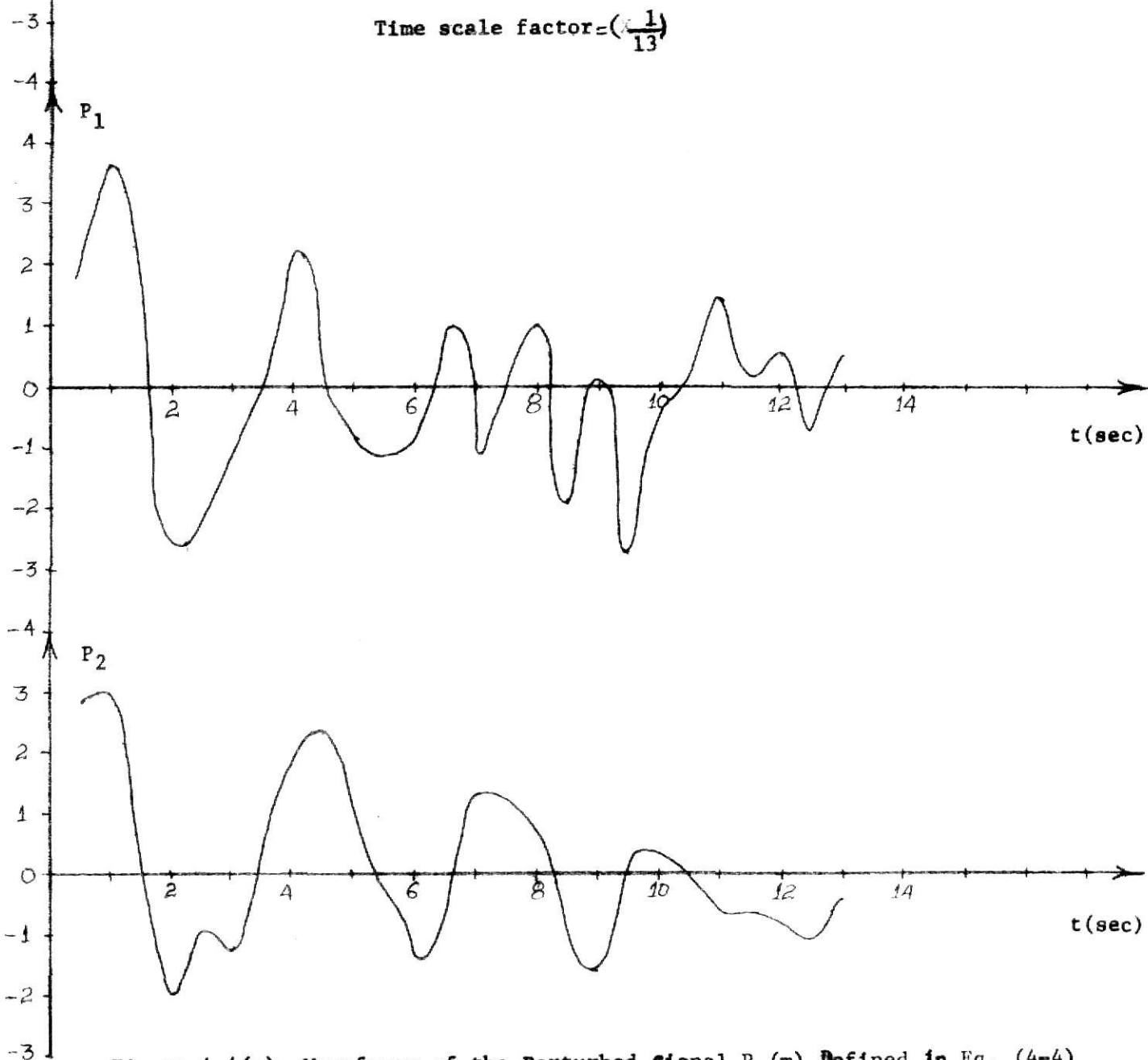
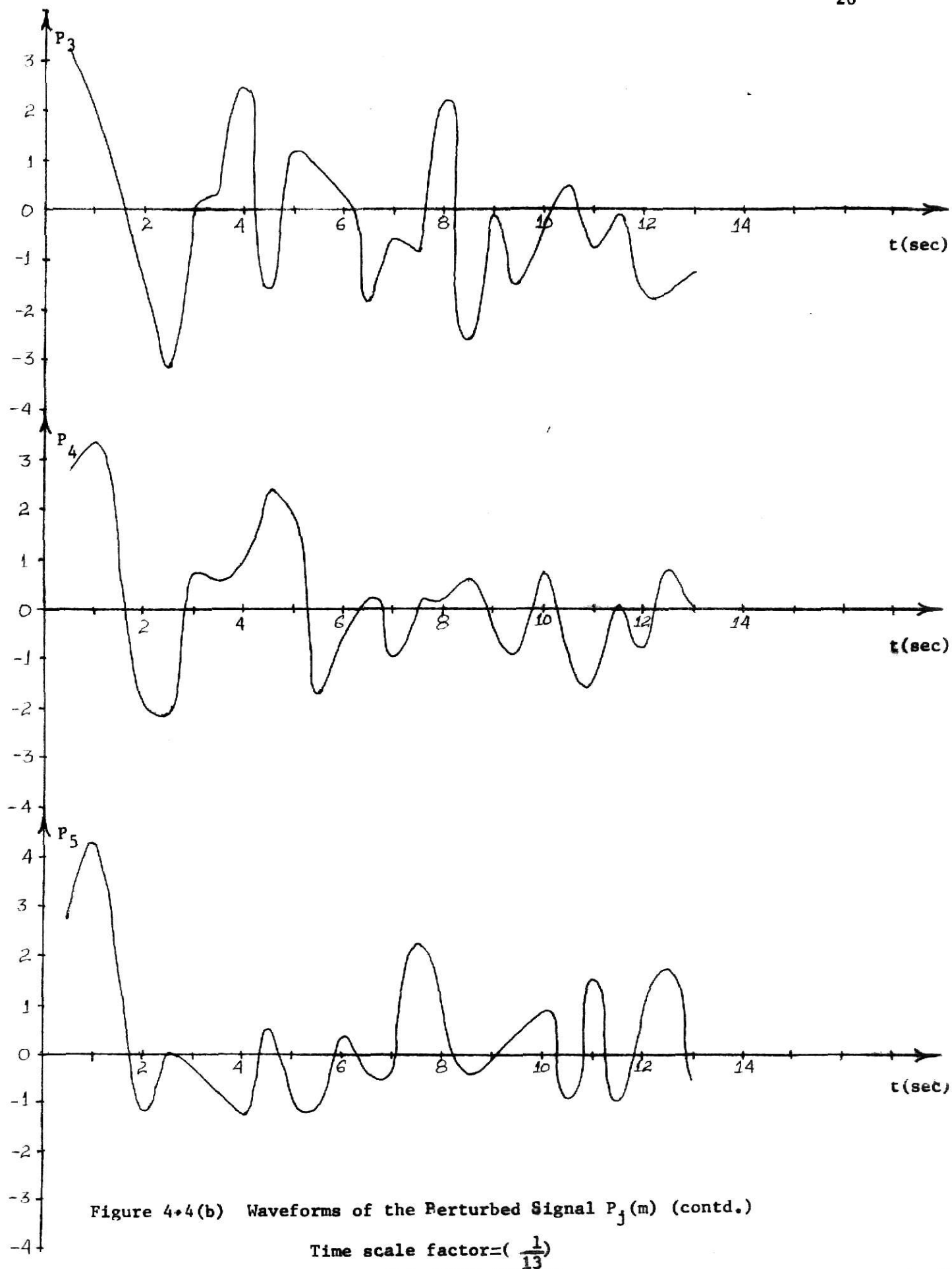
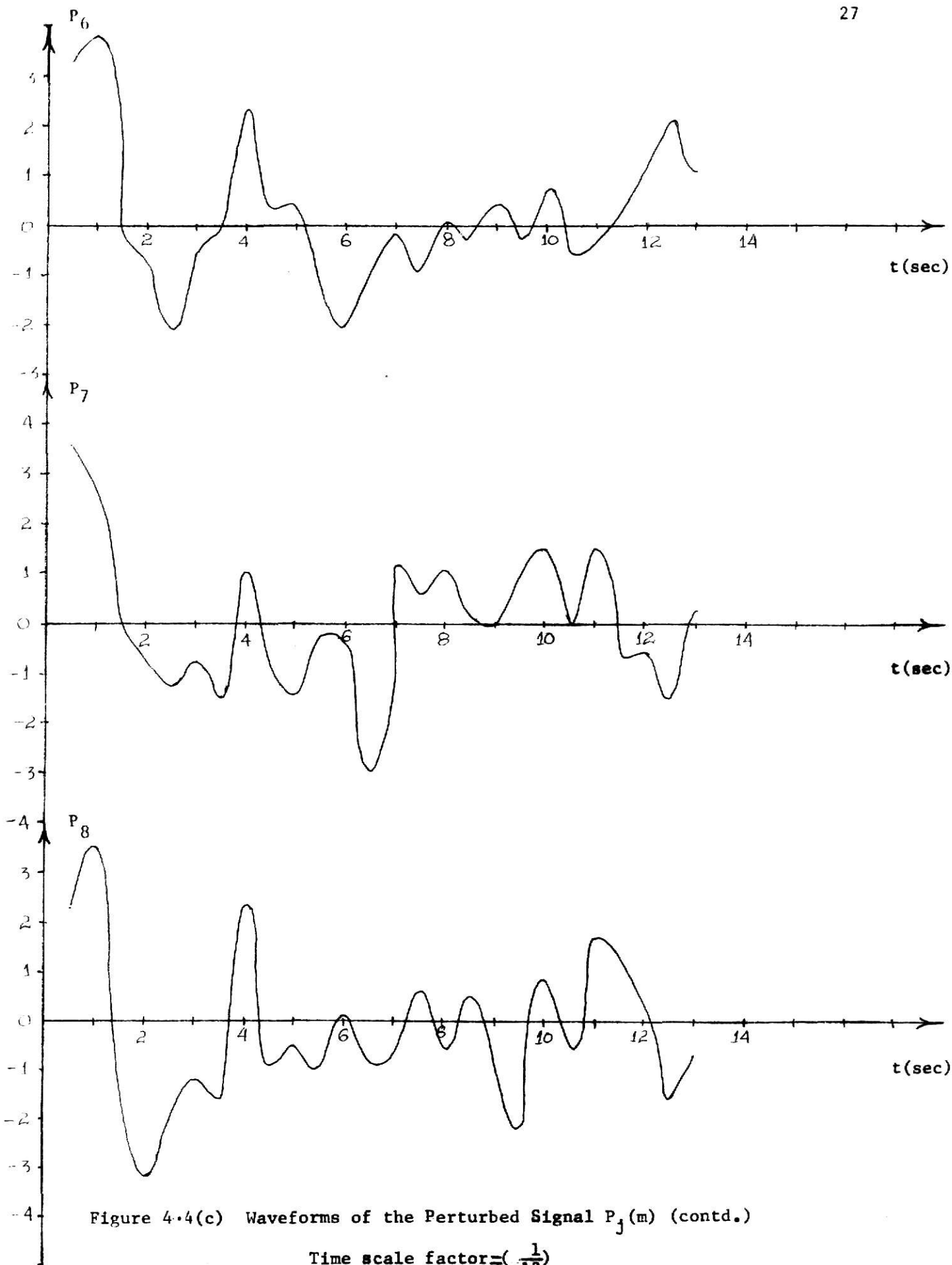


Figure 4-4(a) Waveforms of the perturbed signal $P_j(m)$ Defined in Eq. (4-4)

Time scale factor = $(\frac{1}{13})$





the ensemble of perturbed signal as

$$P_j(m) = S(m) + N_j(m) \quad m=1,2,\dots,26 \quad (4-4)$$

where $N_j(m)$ denotes the j -th noise sample.

The scale factor 3.97 associated with $S(m)$ in Eq. (4-3) was chosen such that the mean-square value of $S(m)$ is approximately equal to that of the noise ensemble.

That is,

$$\sum_{m=1}^{26} S^2(m) \approx \frac{1}{8} \sum_{j=1}^8 \sum_{m=1}^{26} N_j^2(m) \quad (4-5)$$

The Fourier power spectrum of the signal $S(m)$ at 20 filters having center frequencies listed in Table 4-1 is given by

$$P(\omega_n, N-1) = (\Delta t)^2 \left| \underline{Z}(\omega_n, N-1) \right|^2 \quad n=1,2,\dots,20$$

$$N=26, \Delta t = \frac{1}{26} \text{ sec} \quad (4-6)$$

where

$$\underline{Z}(\omega_n, N-1) = \sum_{m=0}^{N-1} \left[L(\omega_n) \right]^m \underline{b} S(m) \quad (4-7)$$

$\underline{Z}(\omega_n, N-1)$ is obtained using the recurrence relation in Eq. (2-9) as

$$\underline{Z}(\omega_n, k) = \left[L(\omega_n) \right] \underline{Z}(\omega_n, k-1) + \underline{b} X(N-1-k) \quad k=0,1,\dots,26 \quad (4-8)$$

where

$X(N-1-k)$ is replaced by $S(27-m)$, $m=1,2,\dots,26$

and

$$\left[L(\omega_n) \right] = \begin{bmatrix} \cos(\omega_n \Delta t) & -\sin(\omega_n \Delta t) \\ \sin(\omega_n \Delta t) & \cos(\omega_n \Delta t) \end{bmatrix} \quad (4-9)$$

Next, the following computations were performed*:

(1) The Fourier power spectrum of $S(m)$ defined in Eq. (4-6) was obtained using the recurrence relation in Eq. (4-8).

(2) The Fourier power spectra of the samples of the perturbed signal $P_j(m), j=1,2,\dots,8$ were obtained using the recurrence relation defined in Eq. (4-8) with $X(N-1-k)$ replaced by $P_j(27-m), m=1,2,\dots,26, j=1,2,\dots,8$ at the frequencies listed in Table (4-1).

(3) The smoothed power spectra of the samples of the perturbed signal $P_j(m), j=1,2,\dots,8$ were obtained using 20 damped filters having the same center frequencies using the recurrence relation in Eq. (4-8) with $X(N-1-k)$ replaced by $P_j(27-m), m=1,2,\dots,26, j=1,2,\dots,8$ and

$$\begin{bmatrix} L(\omega_n) \end{bmatrix} = \begin{bmatrix} e^{-\alpha\Delta t} \cos(\omega_c \Delta t) & -e^{-\alpha\Delta t} \sin(\omega_c \Delta t) \\ e^{-\alpha\Delta t} \sin(\omega_c \Delta t) & e^{-\alpha\Delta t} \cos(\omega_c \Delta t) \end{bmatrix}$$

where

$$\begin{aligned} \alpha &= \zeta \omega_n \\ \omega_c &= \omega_n \sqrt{1-\zeta^2} \\ \zeta &= 0.0588 \end{aligned} \tag{4-10}$$

The above value of ζ was obtained using Eq. (2-20). Thus Eq. (2-19) implies that each filter has a $Q=1/2\zeta=8.5$.

The Fourier power spectrum points of the signal $S(m)$ and the power spectra of a typical perturbed signal $P_1(m)$ without smoothing and with smoothing are tabulated in Table (4-3). Also, the mean-square errors of the above spectra with respect to the Fourier power spectrum of the signal $S(m)$ are tabulated in Table (4-3).

*For a listing of the computer program, see Appendix III.

TABLE 4-3

Frequency Hz	1.38	1.5	1.7	1.96	2.2	2.48	2.8	3.14	3.5
Fourier Power Spectrum of the Signal-S(m) $\left[\cdot \left(\frac{1}{26} \right)^2 \right]$	17.5	18.9	20.0	22.0	26.0	34.0	43.0	63.0	103.0
Unsmoothed Power Spectrum of the First Sample of the Perturbed Signal-P ₁ (m) $\left[\cdot \left(\frac{1}{26} \right)^2 \right]$ Mean Square Error	10.0 .0151	0.9 .0132	14.0 .0080	54.0 .0038	88.0 .0068	71.0 .0075	190 .0058	69.0 .0219	249.0 .0266
Smoothed Power Spectrum ($\zeta=0.0588$) of P ₁ (m) $\left[\cdot \left(\frac{1}{26} \right)^2 \right]$ Mean Square Error	10.7 0.0082	4.7 0.0069	14.0 .0043	38.0 .0025	58.0 .0028	52.0 .0020	34.0 .0013	61.0 .0037	140.0 .0033
Power Spectrum of P ₁ (m) Smoothed Using Hanning's Algorithm $\left[\cdot \left(\frac{1}{26} \right)^2 \right]$ Mean Square Error	16.22 .0094	6.45 .0118	20.72 .0073	52.5 .0042	75.25 .0052	62.25 .0046	44.5 .0055	101.5 .0142	218.5 .0163

TABLE 4-3 (Cont.)

3.97	4.47	5.	5.65	6.36	7.2	8.	9.	10.2	11.5	12.89
137.0	91.0	37.0	17.0	8.7	4.7	2.9	1.9	1.4	1.2	1.0
307.0	97.0	122.0	72.0	7.0	16.0	22.0	2.4	57.0	28.0	44.0
.0242	.0097	.0088	.0053	.0005	.0058	.0049	.0004	.0035	.0012	.0061
157.0	90.0	72.0	36.0	10.8	12.0	8.7	2.1	1.8	0.5	0.02
.0042	.0029	.0011	.0005	.0001	.0005	.0003	.0000	.0000	.0000	.0000
240.	155.75	103.25	68.25	25.5	15.25	15.6	20.95	36.1	39.25	31.5
.0092	.0036	.0033	.0032	.0016	.0027	.0027	.0014	.0015	.0020	0.0050

The usual practice to smooth the power spectrum against a random process is to average the spectrum over neighbouring frequencies. A particular case is the discrete-time Hanning smoothing algorithm given by,

$$P(\omega_n, N-1) = \frac{1}{4}P(\omega_{n-1}, N-1) + \frac{1}{2}P(\omega_n, N-1) + \frac{1}{4}P(\omega_{n+1}, N-1) \quad (4-11)$$

The Hanning smoothed power spectrum points for a typical perturbed signal $P_1(m)$ and the corresponding mean-square errors are also listed in the Table (4-3). It is remarked that Hanning smoothing algorithm is as effective as any of the other smoothing algorithms for run-of-the-mill problems [2].

The mean-square errors corresponding to the unsmoothed power spectra, the smooth power spectra and Hanning smoothed power spectra of the set of 8 perturbed signals (see Figure 4.4) are plotted in Figure 4.5.

From the Figure 4.5 it can be observed that the smoothed power spectrum of the perturbed signal $P_j(m)$ obtained using the damped filters gives the best spectral estimate of $P_j(m)$ with the least error.

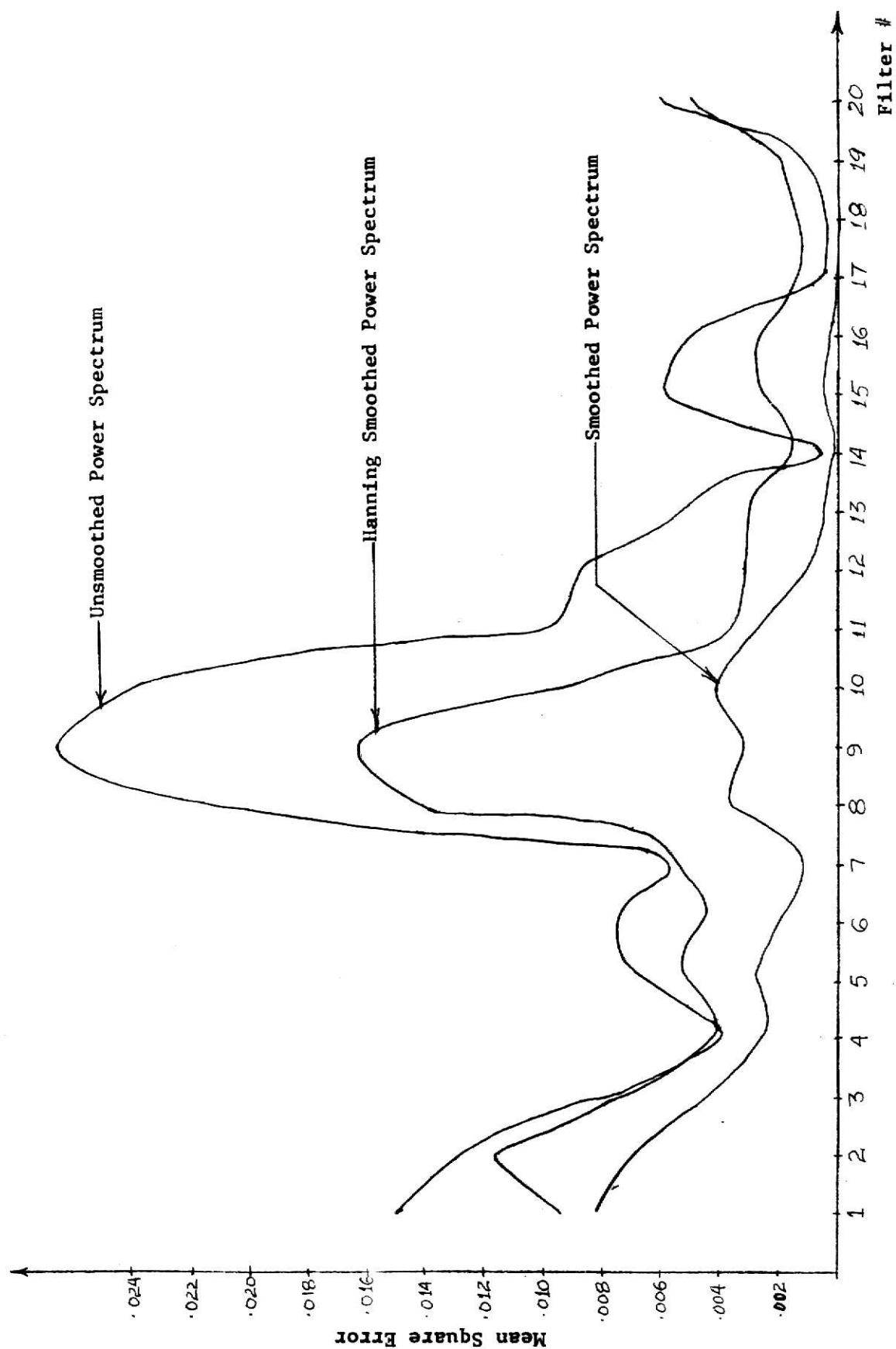


Figure 4.5 Summary of Errors in Spectral Estimation

CHAPTER V

CONCLUSION

This report has presented a study of the possible applications of Arnold's algorithm and the time-varying Fourier transform. It has been demonstrated that Arnold's algorithm can be used in situations where transient waveforms, embedded in noise, have to be classified via pattern classification techniques. Then it is shown that the time-varying Fourier transform can be used for two purposes: (1) to compute the Fourier transform of a discrete signal, and (2) to estimate the Fourier power and phase spectra of transient waveforms embedded in noise. Both of these spectra can be obtained recursively with any desired frequency resolution.

Several areas are open for further work. Arnold's on-line computational algorithm might be extended to two-dimensions and hence applied to image processing. Specifically it could prove to be useful in classifying two-dimensional patterns, embedded in noise.

It is apparent that the time-varying Fourier transform could be used to estimate the correlation and convolution functions associated with discrete signals in the presence of noise. As such it could prove useful in the area of digital filtering and hence deserves to be investigated and compared with the techniques which are presently available.

By means of a simulated experiment, it has been demonstrated that the time-varying Fourier transform yields superior spectral estimates when compared with a standard smoothing technique such as that attributed to Hanning. The logical question which arises is whether this is the case in

general at various signal-to-noise ratios. It would be very worthwhile to investigate this problem using methods which are used in the area of statistical communication theory.

APPENDIX I

In this appendix, a listing of FORTRAN IV Computer program which implements Arnold's on-line computational algorithm (Eq. (2-24)) to compute the instantaneous power points of the first sample of the signals belonging to Class A (see Figure 4-1) is provided.

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MAIN

FORTPAN IV G LEVEL 19

```

0026 2',,10X,'COUNT',10X,'CENTER FREQUENCY',18X,'BANDWIDTH',18X,'3 DB C
0027 CROSS OVER PT. '/')
0028 DO 200 K=1,KK
0029 KP1=K+1
0030 IF(K.NE.KK) GO TO 45
0031 FCP1=FACT*FREQ(KK)
0032 CROSS=SQRT(FREQ(KK)*FROP1)
0033 GO TO 50
0034 45 CROSS=SQRT(FREQ(K)*FREQ(KP1))
0035 50 PRINT 55,K,FREQ(K),HAND,CROSS
0036 55 FORMAT(' ',10X,I3,10X,F12.6,20X,F10.4,20X,F10.4)
0037 100 CONTINUE
0038 GO TO 75
0039 60 IF(IIDFT.NE.1) GO TO 65
0040 PRINT 160
0041 160 FORMAT('1',10X,'FOURIER POWER SPECTRUM AT HARMONIC FREQUENCIES')
0042 C. CALCULATE THE HARMONIC FREQUENCIES
0043 FREQ(1)=0.
0044 KK=N/2+1
0045 AK=N
0046 DO 150 I=2,KK
0047 FREQ(K)=(AK-1.)/(A1*DT)
0048 150 CONTINUE
0049 GO TO 75
0050 C READ THE CHOSEN FREQUENCIES
0051 65 READ 70,KK,(FREQ(K),K=1,KK)
0052 70 FORMAT(13/(F10.2))
0053 PRINT 165,(FREQ(K),K=1,KK)
0054 165 FORMAT('1',10X,'FOURIER POWER SPECTRUM AT THE CHOSEN FREQUENCIES')
0055 1/, ' ',THE CHOSEN FREQUENCIES ARE...//(' ',10F10.2))
0056 75 TPDT=6.28318*DT
0057 C COMMENT-TPDT IS TWO PI DELTA T
0058 RHMZ=SQRT(1.0-ZETA**2)
0059 READ THE INPUT DATA
0060 80 READ (5,200,END=1000) (X(I),I=1,N)
0061 200 FORMAT(16F5.2)
0062 PRINT 250,(X(I),I=1,N)
0063 250 FORMAT('C',,INPUT SAMPLED DATA: '/(' ',10F10.2))
0064 DO 500 K=1,KK
0065 ARG=TPDT*FREQ(K)
0066 EXX=EXP(-ZETA*ARG)
0067 CC=EXX*COS(ROMZ*ARG)
0068 SS=EXX*SIN(ROMZ*ARG)
0069 L=J+1
0070 C INITIALISE THE FILTERS
0071 DO 300 M=1,L
0072 Z1(M)=0.
0073 Z2(M)=0.
0074 300 CONTINUE
0075 PRINT 85,K,FREQ(K)
0076 85 FORMAT('C',,FILTER #=' ',I3,10X,'FREQUENCY =' ',F10.3)
0077 IF(INI.EC.0) GO TO 95
0078 PRINT 90
0079 90 FORMAT('C',10X,'INSTANT OF TIME',12X,'INSTANTANEOUS POWER')
0080 95 CONTINUE
0081 DO 400 M=1,N

```

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FORTRAN IV 6 LEVEL 18

MAIN

(Arnold's Algorithm)

```

0076 C COMPUTE THE TIME-VARYING POWER
0077 Z1(M+1)=CC*Z1(M)-SS*Z2(M)
0078 Z2(M+1)=SS*Z1(M)+CC*Z2(M)+X(M)
0079 POWER(K)=Z1(M+1)**2+Z2(M+1)**2
0080 IF (INT,EC=J) GO TO 400
0081 IF (INT,EC=J) GO TO 110
0082 A=M
0083 AINT=INT
0084 KINT=M/AINT
0085 K=KINT
0086 HRR=K
0087 IF (KINT.NE.HRR) GO TO 400
0088 PRINT 115,M,POWER(K)
0089 115 FORMAT(' ',15X,13,20X,F12.6)
0090 400 CONTINUE
0091 PRINT 120,POWER(K)
0092 120 FORMAT(' ',10X,'TOTAL POWER=',F12.4)
0093 500 CONTINUE
0094 C RETURN TO READ NEXT SET OF INPUT DATA
0095 GO TO 80
0096 1000 CONTINUE
0097 STOP
0098 E 40

```

SMOOTHED POWER SPECTRUM

DELTA T = 0.3385 ZETA = 0.0388 FREQUENCY RANGE = 1. DECADE(S)

THE COMPUTED FREQUENCIES ARE.....

BASE = 1.300

NYQUIST = 13.000

TABLE OF FILTER CENTER FREQUENCIES

COUNT	CENTER FREQUENCY	BANDWIDTH	3 DB CROSS OVER PT.
1	1.376456	0.1619	1.4599
2	1.548440	0.1821	1.6423
3	1.741910	0.2048	1.8475
4	1.959554	0.2304	2.0784
5	2.204391	0.2592	2.3381
6	2.479819	0.2916	2.6302
7	2.789661	0.3281	2.9586
8	3.138217	0.3691	3.3285
9	3.530323	0.4152	3.7444
10	3.971421	0.4670	4.2122
11	4.467632	0.5254	4.7385
12	5.025843	0.5910	5.3306
13	5.653799	0.6649	5.9966
14	6.360216	0.7480	6.7459
15	7.154897	0.8414	7.5887
16	8.048869	0.9465	8.5359
17	9.054540	1.0648	9.6036
18	10.185864	1.1979	10.8035
19	11.458544	1.3475	12.1533
20	12.890239	1.5159	13.6718

INPUT SAMPLED DATA:

-3.23	-0.03	1.38	-0.62	1.24	0.24	-0.94	0.97	0.91	-1.19
-0.70	-0.17	-0.66	1.23	-0.13	-0.52	-0.46	-0.52	0.98	-1.38
-0.07	0.98	-1.69	0.39	-2.60	-0.41	-0.06	1.36	0.27	0.62
-0.59	0.56	0.27	-1.21	-0.31	-1.56	0.60	1.29	0.17	-0.11
-0.11	-0.29	0.72	0.24	0.20	-0.88	0.60	0.26	-0.97	0.98

FILTER # = 1 FREQUENCY = 1.376

INSTANT OF TIME

10	INSTANTANEOUS POWER
20	8.123537
30	9.300437
40	8.603025
50	3.545267
	3.309862

TOTAL POWER = 3.3099

FILTER # = 2 FREQUENCY = 1.546

INSTANT OF TIME

10	INSTANTANEOUS POWER
20	10.041385
30	7.455791
	1.888959

40		1.880022	
50		1.265900	
TOTAL POWER=		1.2629	
FILTER #=	3	FREQUENCY =	1.742
INSTANT OF TIME		INSTANTANEOUS POWER	
10		12.081050	
20		5.088265	
30		7.986492	
40		0.715280	
50		0.474867	
TOTAL POWER=		0.4749	
FILTER #=	4	FREQUENCY =	1.960
INSTANT OF TIME		INSTANTANEOUS POWER	
10		13.962620	
20		4.703764	
30		26.823968	
40		23.409464	
50		6.144091	
TOTAL POWER=		8.1441	
FILTER #=	5	FREQUENCY =	2.204
INSTANT OF TIME		INSTANTANEOUS POWER	
10		15.203162	
20		8.282079	
30		33.921699	
40		34.612427	
50		21.490356	
TOTAL POWER=		21.4904	
FILTER #=	6	FREQUENCY =	2.460
INSTANT OF TIME		INSTANTANEOUS POWER	
10		15.191533	
20		13.645615	
30		13.069179	
40		23.580948	
50		11.518242	
TOTAL POWER=		11.5182	
FILTER #=	7	FREQUENCY =	2.790
INSTANT OF TIME		INSTANTANEOUS POWER	
10		13.439216	
20		14.172773	
30		4.908609	
40		15.703625	
50		4.992037	
TOTAL POWER=		4.9950	
FILTER #=	8	FREQUENCY =	3.132
INSTANT OF TIME		INSTANTANEOUS POWER	
10		10.132767	
20		7.310241	
30		10.963729	

40		29.386429
50		7.053221
TOTAL POWER= 7.0592		
FILTER #= 9	FREQUENCY = 3.530	
INSTANT OF TIME		
10	INSTANTANEOUS POWER	
20	6.780526	
30	1.114478	
40	18.599991	
50	5.026380	
TOTAL POWER= 4.3461		
FILTER #= 10	FREQUENCY = 3.971	
INSTANT OF TIME		
10	INSTANTANEOUS POWER	
20	6.168399	
30	0.556690	
40	12.951870	
50	0.906883	
TOTAL POWER= 1.8827		
FILTER #= 11	FREQUENCY = 4.468	
INSTANT OF TIME		
10	INSTANTANEOUS POWER	
20	10.279009	
30	3.619137	
40	6.695562	
50	12.623339	
TOTAL POWER= 6.9989		
FILTER #= 12	FREQUENCY = 5.026	
INSTANT OF TIME		
10	INSTANTANEOUS POWER	
20	16.341583	
30	14.792209	
40	6.084167	
50	14.380816	
TOTAL POWER= 3.8972		
FILTER #= 13	FREQUENCY = 5.654	
INSTANT OF TIME		
10	INSTANTANEOUS POWER	
20	16.204559	
30	10.572622	
40	6.975485	
50	8.724563	
TOTAL POWER= 3.2461		
FILTER #= 14	FREQUENCY = 6.360	
INSTANT OF TIME		
10	INSTANTANEOUS POWER	
20	9.824695	
30	2.027374	
40	1.649444	

40	29.386429		
50	7.053221		
TOTAL POWER=	7.0592		
FILTER #= 9	FREQUENCY =	3.530	
INSTANT OF TIME	INSTANTANEOUS POWER		
10	6.78056		
20	1.114478		
30	18.599991		
40	5.026360		
50	4.346114		
TOTAL POWER=	4.3461		
FILTER #= 10	FREQUENCY =	3.971	
INSTANT OF TIME	INSTANTANEOUS POWER		
10	6.168399		
20	0.556690		
30	12.951870		
40	0.906883		
50	1.882741		
TOTAL POWER=	1.8827		
FILTER #= 11	FREQUENCY =	4.468	
INSTANT OF TIME	INSTANTANEOUS POWER		
10	10.279003		
20	3.619137		
30	6.695562		
40	12.623339		
50	6.998896		
TOTAL POWER=	6.9989		
FILTER #= 12	FREQUENCY =	5.026	
INSTANT OF TIME	INSTANTANEOUS POWER		
10	16.341553		
20	14.792209		
30	6.084167		
40	12.390816		
50	3.897155		
TOTAL POWER=	3.8972		
FILTER #= 13	FREQUENCY =	5.654	
INSTANT OF TIME	INSTANTANEOUS POWER		
10	16.204559		
20	10.572622		
30	6.975285		
40	8.724563		
50	3.246077		
TOTAL POWER=	3.2461		
FILTER #= 14	FREQUENCY =	6.360	
INSTANT OF TIME	INSTANTANEOUS POWER		
10	6.829695		
20	2.027371		
30	1.046444		

40	1.051954
50	2.103821
TOTAL POWER= 2.1030	
FILTER #= 15 FREQUENCY = 7.155	
INSTANT OF TIME	INSTANTANEOUS POWER
10	2.197970
20	3.302446
30	0.027491
40	1.239677
50	3.062873
TOTAL POWER= 3.0629	
FILTER #= 16 FREQUENCY = 8.049	
INSTANT OF TIME	INSTANTANEOUS POWER
10	12.663522
20	6.639526
30	1.992380
40	2.375566
50	6.960953
TOTAL POWER= 6.9610	
FILTER #= 17 FREQUENCY = 9.055	
INSTANT OF TIME	INSTANTANEOUS POWER
10	14.562389
20	1.291921
30	4.700649
40	2.431132
50	4.971066
TOTAL POWER= 4.9711	
FILTER #= 18 FREQUENCY = 10.186	
INSTANT OF TIME	INSTANTANEOUS POWER
10	1.978825
20	7.870586
30	1.462383
40	2.011731
50	6.918830
TOTAL POWER= 6.9189	
FILTER #= 19 FREQUENCY = 11.459	
INSTANT OF TIME	INSTANTANEOUS POWER
10	2.122783
20	7.284651
30	5.017847
40	1.728312
50	3.050638
TOTAL POWER= 3.0508	
FILTER #= 20 FREQUENCY = 12.890	
INSTANT OF TIME	INSTANTANEOUS POWER
10	6.500082
20	3.724787
30	7.516002

0.035832
C.884828

40
50
TOTAL POWER= 0.8848

APPENDIX II

This appendix provides a listing of a computer program for a training algorithm which uses the least-square mapping principle to classify two classes of signals mentioned in Section 4.2.

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MAIN

FCRTRAN IV G LEVEL 18

```

C
C      # OF CLASSES: MAX. 1C
C      # OF SAMPLES IN EACH CLASS: MAX. 1CC
C      DIMENSION OF SAMPLES & UNIT VECTORS: MAX. 2C
C      FIRST CARD IN THE MAIN PROGRAM SHOULD BE CHANGED DEPENDING ON THE
C      COMPILER USED
C      FIRST DATA CARD: # OF CLASSES, DIMENSIONS OF SAMPLES & UNIT VECTORS IN 315
C      SECOND CARD : # OF SAMPLES IN EACH CLASS IN FORMATS CF 15
C      THIRD CARD : PROBABILITY OF EACH CLASS IN FORMATS CF FR.4
C      READ IN UNIT VECTORS , ONE PER CARD, EACH COMPONENT IN FR.4
C      SAMPLES , ONE PER CARD, WITH COMPONENTS IN FR.4
C
C001 DATA NR,NW/5,6/
C002 DIMENSION NSAMP(10),PRCB(10),V(10,10),X(21,100),P(2100,10)
C003 DIMENSION Y(21,21),XX(21,21),A(10,21),E(10,21),VX(10,21),C(10,100)
C004 DIMENSION ICF(10,10)
C005 READ(NR,1)NCLAS,NCCPP,LV
C006 FORMAT(10I5)
C007 WRITE(NR,2)NCLAS,NCCOMP
C008 FORMAT(10X,'THIS PROBLEM HAS',15,' CLASSES & EACH CLASS IS',15,
C009 1,' DIMENSIONAL',15)
C009 N=NCLAS
C010 READ(NR,1)(NSAMP(I),I=1,N)
C011 READ(NR,20)(PPCB(I),I=1,N)
C012 FORMAT(10F8.4)
C013 CO 4 I=1,N
C014 WRITE(NR,5)I,NSAMP(I),PPCB(I)
C015 FORMAT(10X,'CLASS',15,' HAS',15,' SAMPLES & ITS PROBABILITY
C016 LIS',F10.4)
C016 L=NCCOMP
C017 CO 10 J=1,N
C018 READ (NR,20)(V(I,J),I=1,LV)
C019 FORMAT(10F8.4)
C020 WRITE(NR,3)
C021 WRITE(NR,25)
C022 FORMAT(10X,' V MATRIX',15)
C023 CO 30 I=1,LV
C024 WRITE(NR,35)(V(I,J),J=1,N)
C025 FORMAT(10X,11F10.3)
C026 LI=L+1
C027 CO 80 K=1,N
C028 NI=NSAMP(K)
C029 FI=FLCAT(NI)
C030 FI=PPCB(K)
C031 CO 40 J=1,NI
C032 READ(NR,20)(X(I,J),I=1,L)
C033 P(LI,J)=1.0
C034 P=1
C035 CO 41 J=1,NI
C036 CO 41 I=1,L1
C037 F(V,K)=X(I,J)
C038 P=P+1
C039 WRITE(NR,3)
C040 WRITE(NR,45)K
C041 FORMAT(10X,'AUGMENTED PATTERNS OF CLASS',15,15)
C042 CO 50 I=1,L1
C043 WRITE(NR,35)(X(I,J),J=1,NI)
C044 CO 60 I=1,L1

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C045 CC 60 I2=1,L1
C046 Y(I1,I2)=0.0
C047 CC 55 J=1,N1
C048 55 Y(I1,I2)=Y(I1,I2)+X(I1,J)*X(I2,J)
C049 Y(I1,I2)=PI*Y(I1,I2)/FI
C050 IF(K-EC-1)*X(I1,I2)=0.0
C051 60 X(I1,I2)=X(I1,I2)+Y(I1,I2)
C052 CC 65 I=1,L1
C053 CC 65 J=2,N1
C054 65 X(I1,I2)=X(I1,I2)+X(I1,J)
C055 CC 70 I=1,LV
C056 CC 70 J=1,L1
C057 A(I1,J)=PI*V(I1,K)*X(J,I)/FI
C058 IF(K-EC-1)*X(I1,J)=0.0
C059 70 X(I1,J)=VX(I1,J)+A(I1,J)
C060 80 CONTINUE
C061 CALL INVER(X,X,L1)
C062 CC 120 I=1,LV
C063 CC 120 J=1,L1
C064 A(I1,J)=0.0
C065 CC 120 K=1,L1
C066 120 A(I1,J)=A(I1,J)+VX(I1,K)*XX(K,J)
C067 WRITE(NW,3)
C068 WRITE(NW,125)
C069 125 FORMAT(10X,'TRANSFORMATION MATRIX A'///)
C070 CC 130 I=1,LV
C071 130 WRITE(NW,35)(A(I1,J),J=1,L1)
C072 CC 135 I=1,N
C073 CC 135 J=1,L1
C074 E(I1,J)=0.0
C075 CC 135 K=1,LV
C076 135 E(I1,J)=E(I1,J)+V(K,I)*A(K,J)
C077 WRITE(NW,3)
C078 WRITE(NW,140)
C079 140 FORMAT(10X,'PRECISION MATRIX'///)
C080 CC 142 I=1,N
C081 142 WRITE(NW,35)(F(I1,J),J=1,L1)
C082 CC 145 I=1,N
C083 CC 145 J=1,N
C084 ICF(I,J)=0
C085 CC 185 K=1,N
C086 NI=NSAMP(K)
C087 P=1
C088 CC 150 J=1,N1
C089 CC 150 I=1,L1
C090 X(I1,J)=P(M,K)
C091 P=M+1
C092 CC 160 I=1,N
C093 CC 160 J=1,N1
C094 C(I1,J)=0.0
C095 CC 160 M=1,L1
C096 160 C(I1,J)=C(I1,J)+E(I1,M)*X(M,J)
C097 WRITE(NW,3)
C098 CC 161 ID=1,N
C099 161 WRITE(NW,35)(F(IC,JD),JD=1,N1)
C100 CC 180 J=1,N1
C101 LS=1
C102 C=C(I1,J)

```

```

FCRTRAN IV G LEVEL 18          MAIN          DATE = 72C94          18/35/34          PAGE C003

C103      CC 17C I=1,N
C104      IF(C-LT-D(I,J))GO TO 165
C105      CC TC 170
C106      165  LS=I
C107      C=D(I,J)
C108      17C CONTINUE
C109      180  ICF(K,LS)=ICF(K,LS)+1
C110      185  CONTINUE
C111      WRITE(NM,3)
C112      WRITE(NM,190)
C113      FORMAT(10X,'CONFUSION MATRIX'////)
C114      CO 195 I=1,N
C115      195  WRITE(NM,2CC)(ICF(I,J),J=1,N)
C116      200  FORMAT(10X,1C15)
C117      STOP
C118      END

```

```

FORTRAN IV G LEVEL 18      INVERS      DATE = 72094      PAGE C001
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C001      SUBROUTINE INVERS(Z,N)
C002      DIMENSION U(21,21),V(21,21),Y(21,21),Z(21,21),Z(21,21)
C003      CC 5 I=1,N
C004      CC 5 J=1,N
C005      U(I,J)=0.C
C006      5 IF (I.EC.J)U(I,J)=1.C
C007      1 L=1
C008      10 K=L
C009      11 C=ABS(Z(K,L))
C010      IF (C=0.C000001)20,20,30
C011      Z(K,L)=0.0
C012      K=K+1
C013      IF (K-N)11,11,90
C014      CC 31 M=1,N
C015      Y(K,M)=Z(K,M)
C016      Z(K,M)=Z(L,M)
C017      Z(L,M)=Y(K,M)
C018      V(K,M)=U(K,M)
C019      L(K,M)=U(L,M)
C020      L(L,M)=V(K,M)
C021      Y(L,L)=Z(L,L)
C022      41 M=1,N
C023      Z(L,M)=Z(L,M)/Y(L,L)
C024      L(L,M)=U(L,M)/Y(L,L)
C025      K=1
C026      IF (K-L)52,51,52
C027      K=K+1
C028      IF (K-N)50,50,70
C029      C=ABS(Z(K,L))
C030      IF (C=0.C00001)53,53,54
C031      53 Z(K,L)=0.0
C032      K=K+1
C033      IF (K-N)50,50,60
C034      Y(K,L)=Z(K,L)
C035      55 M=1,N
C036      Z(K,M)=Z(K,M)-Z(L,M)*Y(K,L)
C037      L(K,M)=U(K,M)-U(L,M)*Y(K,L)
C038      K=K+1
C039      IF (K-N)50,50,60
C040      L=L+1
C041      IF (L-N)10,10,70
C042      70 CC 80 I=1,N
C043      CC 80 J=1,N
C044      80 Z(I,J)=U(I,J)
C045      90 RETURN
C046      END

```

THIS PROBLEM HAS 2 CLASSES & EACH CLASS IS 8 DIMENSIONAL

CLASS 1 HAS 8 SAMPLES & ITS PROBABILITY IS 0.5000
 CLASS 2 HAS 8 SAMPLES & ITS PROBABILITY IS 0.5000

V MATRIX

1.000 0.0
 0.0 1.000

AUGMENTED PATTERNS OF CLASS 1

0.600 7.300 0.800 5.700 6.300 2.600 3.000 4.300
 12.900 3.800 2.300 13.000 0.200 7.700 9.100 1.500
 0.900 11.100 15.200 4.800 7.200 3.500 0.600 8.300
 3.600 17.000 5.600 7.500 0.0 17.600 4.200 9.900
 6.700 18.900 4.400 4.900 0.800 18.900 3.400
 12.600 11.000 20.200 3.000 1.900 8.000 1.700 8.800
 14.800 7.500 3.500 15.300 2.600 14.800 4.200 3.800
 6.000 10.300 16.000 2.600 0.900 3.600 22.000 5.400
 -1.000 -1.000 -1.000 -1.000 -1.000 -1.000 -1.000

AUGMENTED PATTERNS OF CLASS 2

16.400 39.400 35.300 8.800 51.500 9.100 18.600 2.600
 31.000 25.000 7.500 17.000 18.800 5.100 11.200 20.300
 2.800 26.000 30.400 0.300 12.700 14.400 7.900 30.000
 28.400 35.200 46.300 42.700 20.200 35.300 12.200 23.100
 4.500 35.400 1.800 13.600 5.500 15.800 2.000 35.800
 16.700 11.000 6.100 10.800 7.900 11.100 7.300 4.400
 37.600 8.500 37.500 59.400 13.900 47.300 7.600 25.000
 9.900 13.700 16.500 7.100 3.600 14.400 4.100 21.800
 -1.000 -1.000 -1.000 -1.000 -1.000 -1.000 -1.000

TRANSFORMATION MATRIX A

-0.015 -0.013 -0.014 -0.004 -0.001 0.004 -0.018 -0.005 -1.274
 0.015 0.013 0.014 -0.004 -0.001 0.004 -0.018 0.005 0.274

DECISION MATRIX

-0.015	-0.013	-0.014	0.004	-0.001	0.004	-0.018	-0.005	-1.274
0.015	0.013	0.014	-0.004	0.001	-0.004	0.018	0.005	0.274

DECISION NUMBERS

CLASS 1	0.848	0.887
	0.152	0.113

0.701	0.972
0.259	0.028

1.034	0.908
-0.034	0.092

0.937	1.060
0.063	-0.060

1.060	1.060
-0.060	-0.060

CLASS 2	0.035	-0.043
	0.965	1.043

0.012	-0.178
0.988	1.178

-0.077	0.142
1.077	0.857

0.662	0.099
0.338	0.901

0.099	0.099
0.901	0.901

CONFUSION MATRIX

8	C
1	7

APPENDIX III

In this appendix, a listing of the Computer program which implements the algorithm defined in Eq. (2-9) to compute the Fourier transform power spectrum. The outputs consist of the following (see Table 4-3):

1. Fourier power spectrum of signal $S(m)$ defined in Eq. (4-3).
2. Unsmoothed power spectrum of the first sample of the perturbed signals -- $P_1(m)$ defined in Eq. (4-4).
3. Smoothed power spectrum of $P_1(m)$.

```

1 JCB
2 C
3 C
4 C
5 C
6 C
7 C
8 C
9 C
10 C
11 C
12 C
13 C
14 C
15 C
16 C
17 C
18 C
19 C
20 C
21 C
22 C
23 C
24 C
25 C

COMPLIATION OF TIME-VARYING POWER SPECTRUM

THE FIRST DATA CARD CONTAINS...
  N, THE NUMBER OF INPUT DATA POINTS IN CCLS.1-3, IN 13 FORMAT

THE SECOND DATA CARD CONTAINS...
  DT, THE SAMPLING INTERVAL IN CCLS.1-8, IN F8.4 FORMAT
  ZETA, THE DAMPING FACTOR IN CCLS.5-16, IN F8.4 FORMAT, ZETA=0.
  IMPLIES NO SMOOTHING
  IDFT, FLAG PARAMETER, IN CCL.17, IN 11 FORMAT, IDFT=1 GIVES THE
  POWER SPECTRUM AT THE HARMONIC FREQUENCIES WITH
  ZETA=0., IDFT=C GIVES THE POWER SPECTRUM AT THE
  COMPUTED FREQUENCIES WITH THE GIVEN ZETA OR AT THE
  CHOSEN FREQUENCIES WITH ZETA=C.
  INT, THE INTERVAL OF PRINTING THE TIME-VARYING POWER IN
  CCLS.18-20, IN 13 FORMAT, INT=M IMPLIES THAT THE TIME-
  VARYING POWER WILL BE PRINTED EVERY M-TH INSTANT

THE THIRD DATA CARD CONTAINS...
  DEC, THE DESIRED FREQUENCY RANGE IN DECADES, IN CCLS.1-3, IN
  F3.0 FORMAT, THIRD DATA CARD IS REQUIRED WHEN ZETA IS
  NOT EQUAL TO ZERO

  DIMENSION X(100), Z1(100), Z2(100), FREQ(100), POWER(100)

1 C *** FIRST DATA CARD
2 READ 1C,N
3 10 FORMAT(I3)
4 C *** SECOND DATA CARD
5 READ 15,DT,ZETA,IDFT,INT
6 15 FORMAT(F8.4,I1,I3)
7 IF (ZETA.EC.0.) GO TO 60
8 C *** THIRD DATA CARD
9 READ 2C,DEC
10 20 FORMAT(F3.0)
11 PRINT 25,DT,ZETA,DEC
12 25 FORMAT(11,3CX,'SMOOTHED POWER SPECTRUM',11,10X,'DELTA T =',F6.4
13 1,5X,'ZETA =',F6.4,5X,'FREQUENCY RANGE =',F3.0,' DECADE(S)')
14 CALCULATE FILTER CENTER FREQUENCIES
15 FRNC=C.5/DT
16 COMMENT-FRNC IS THE COMPUTED NYQUIST FREQUENCY
17 FRDS=FRNC/10.##DEC
18 COMMENT-FRDS IS THE BASE FREQUENCY
19 CNPZ=1.##ZETA
20 CNMZ=1.##ZETA
21 FCX=CNFZ*FRBS
22 KK=1
23 FACT=CNPZ/DNMZ
24 FREQ(1)=FCX
25 FCX=FACT*FCX
26 IF (FRNC.LT.FCX) GO TO 35
27 KK=KK+1
28 FREQ(KK)=FCX
29 GO TO 26
30 PRINT THE COMPUTED FREQUENCIES
31 35 PRINT 4C,FRDS,FRNC
32 4C FORMAT(11,5X,'THE COMPUTED FREQUENCIES ARE...',11X,'BASE=',F6.
33 13,11X,'NYQUIST=',F10.3,11X,'TABLE OF FILTER CENTER FREQUENCIES
34 2,11X,'COUNT',10X,'CENTER FREQUENCY',18X,'BANDWIDTH',18X,'3 DB C

```

```

26      3RCSS (VER PT. '/')
27      CC 1CC K=1, KK
28      RANC=2.0*ZETA*FREQ(N)
29      IF(K.NE.KK) GO TO 45
30      FRCPI=FACT*FREQ(KK)
31      CROSS=SQRT(FREQ(KK)*FRCPI)
32      GO TO 5C
33      45 CROSS=SQRT(FREQ(K)*FREQ(KPI))
34      5C PRINT 55,K,FREQ(K),PANC,CROSS
35      55 FORMAT(' ',10X,13,1CX,F12.6,20X,F10.4,20X,F10.4)
36      1CC CCNTINLE
37      CC TC 75
38      6C IF(1CFT.NE.1) GO TO 65
39      PRINT 16C
40      160 FORMAT('1',1CX,'FOURIER POWER SPECTRUM AT HARMONIC FREQUENCIES')
41      C
42      CALCULATE THE HARMONIC FREQUENCIES
43      FREQ(1)=C.
44      KK=N/2+1
45      AN=N
46      AK=K
47      DC 15C I=2, KK
48      FREQ(I)=(AK-1.)/(AN*CI)
49      15C CCNTINLE
50      GO TO 75
51      C
52      READ THE CHOSEN FREQUENCIES
53      65 READ 7C, KK, (FREQ(K), K=1, KK)
54      7C FORMAT(13/(8F10.2))
55      PRINT 165, (FREQ(K), K=1, KK)
56      165 FORMAT('1',1CX,'FOURIER POWER SPECTRUM AT THE CHOSEN FREQUENCIES')
57      17C '1', THE CHOSEN FREQUENCIES ARE...//(' ',10F10.2)
58      75 TPOT=6.28216*CI
59      C
60      COMMENT-TPOT IS TWO PI DELTA T
61      RCMZ=SQRT(1.0-ZETA**2)
62      REAC THE INPUT DATA
63      80 READ (5,20C,END=1CC) (X(1),I=1,N)
64      200 FORMAT(10F8.4)
65      PRINT 250, (X(1),I=1,N)
66      250 FORMAT('C',1CX,'INPUT SAMPLED DATA: '//(' ',10F10.2))
67      CC 5CC K=1, KK
68      ARG=1FCT*FREQ(K)
69      EXX=EXP(-ZETA*ARG)
70      CC=EXX*COS(RCMZ*ARG)
71      SS=EXX*SIN(RCMZ*ARG)
72      L=N+1
73      C
74      INITIALISE THE FILTERS
75      CC 3CC M=1, L
76      Z1(M)=C.
77      Z2(M)=C.
78      300 CCNTINLE
79      PRINT 65,K,FREQ(K)
80      85 FORMAT('C',1CX,'FILTER #=' ,13,1CX,'FREQUENCY =' ,F10.3)
81      IF(INT.EC.C) GO TO 95
82      PRINT 5C
83      9C FORMAT('C',1CX,'INSTANT OF TIME',12X,'INSTANTANEOUS POWER')
84      95 CCNTINLE
85      CC 4CC M=1, N
86      C
87      COMPLETE THE TIME-VARYING POWER
88      Z1(M+1)=CC*Z1(M)-SS*Z2(M)+X(N+1-M)
89      Z2(M+1)=SS*Z1(M)+CC*Z2(M)

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78      POWER(K)=Z1(M+1)**2+Z2(M+1)**2
79      IF(INT.EQ.C) GO TO 4CC
80      IF(INT.EQ.1) GO TO 110
81      AM=N
82      AINT=INT
83      RINT=AM/AINT
84      KR=RINT
85      RKR=KR
86      IF(RINT.NE.RKR) GC TC 400
87      110 PRINT 115,M,POWER(K)
88      115 FORMAT(' ',15X,I3,20X,F12.6)
89      400 CONTINUE
90      PRINT 120,POWER(K)
91      120 FORMAT(' ',10X,'TCTAL POWER=',F12.4)
92      500 CONTINUE
          C      RETURN TO READ NEXT SET OF INPUT DATA
          GC TC 80
          1000 CONTINUE
          STOP
          END
$ENTRY

```

FOURIER POWER SPECTRUM AT THE CHOSEN FREQUENCIES

THE CHOSEN FREQUENCIES ARE...

1.38	1.55	1.74	1.96	2.20	2.48	2.79	3.14	3.50	3.87
4.47	5.03	5.65	6.36	7.15	8.05	9.05	10.15	11.46	12.89

INPUT SAMPLED DATA: S(m)

2.77	2.66	C.58	-1.35	-1.71	-C.68	C.58	1.04	0.59	-C.18
-C.59	-0.44	0.00	0.32	0.21	C.07	-C.15	-C.15	-0.08	C.07
C.12	C.07	-0.02	-0.07	-0.05	0.00				

FILTER # = 1 TOTAL POWER = 17.5316 FREQUENCY = 1.380

FILTER # = 2 TOTAL POWER = 18.8541 FREQUENCY = 1.550

FILTER # = 3 TOTAL POWER = 20.1759 FREQUENCY = 1.740

FILTER # = 4 TOTAL POWER = 22.1253 FREQUENCY = 1.960

FILTER # = 5 TOTAL POWER = 26.2697 FREQUENCY = 2.200

FILTER # = 6 TOTAL POWER = 29.6680 FREQUENCY = 2.480

FILTER # = 7 TOTAL POWER = 43.3884 FREQUENCY = 2.790

FILTER # = 8 TOTAL POWER = 63.3715 FREQUENCY = 3.140

FILTER # = 9 TOTAL POWER = 103.0251 FREQUENCY = 3.500

FILTER # = 10 TOTAL POWER = 136.8965 FREQUENCY = 3.870

FILTER # = 11 TOTAL POWER = 51.2525 FREQUENCY = 4.470

FILTER # = 12 TOTAL POWER = 36.6051 FREQUENCY = 5.030

FILTER # = 13 TOTAL POWER = 17.2301 FREQUENCY = 5.650

FILTER # = 14 TOTAL POWER = 8.6547 FREQUENCY = 6.360

FILTER # = 15 TOTAL POWER = 4.7345 FREQUENCY = 7.150

FILTER # = 16 TOTAL POWER = 2.8977 FREQUENCY = 8.050

FILTER #= 17	FREQUENCY =	9.05C							
TOTAL POWER=	1.9288								
FILTER #= 18	FREQUENCY =	10.19C							
TOTAL POWER=	1.4204								
FILTER #= 19	FREQUENCY =	11.46C							
TOTAL POWER=	1.1871								
FILTER #= 20	FREQUENCY =	12.89C							
TOTAL POWER=	1.0336								
CCRE USAGE	OBJECT CODE=	5368 BYTES,ARRAY AREA=	2000 BYTES,TOTAL AREA AVAILABLE=	49504	BYTES				
DIAGNOSTICS	NUMBER OF ERRORS=	G,	NUMBER OF WARNINGS=	C,	NUMBER OF EXTENSIONS=	0			
CCMPLE TIME=	5.41 SEC,EXECUTION TIME=	2.64 SEC,	WATFIV - VERSION 1	LEVEL 3	MARCH 1971	DATE=	72/094		

FOURIER POWER SPECTRUM AT THE CHOSEN FREQUENCIES

THE CHOSEN FREQUENCIES ARE....

1.38	1.55	1.74	1.96	2.20	2.48	2.79	3.14	3.50	3.97
4.47	5.03	5.65	6.36	7.13	8.05	9.05	10.19	11.46	12.89

INPUT SAMPLED DATA: $P_1(m)$

1.83	3.62	1.49	-2.54	-2.41	-0.84	-0.08	2.27	0.45	-0.64
-1.05	-0.96	0.98	-1.07	0.24	1.34	-1.85	0.19	-2.67	-0.54
0.07	1.43	0.24	0.55	-0.64	0.56				

FILTER # = 1	FREQUENCY = 1.380
TOTAL POWER =	10.1119

FILTER # = 2	FREQUENCY = 1.550
TOTAL POWER =	0.8515

FILTER # = 3	FREQUENCY = 1.740
TOTAL POWER =	14.0882

FILTER # = 4	FREQUENCY = 1.960
TOTAL POWER =	53.6911

FILTER # = 5	FREQUENCY = 2.200
TOTAL POWER =	88.3181

FILTER # = 6	FREQUENCY = 2.480
TOTAL POWER =	71.1964

FILTER # = 7	FREQUENCY = 2.790
TOTAL POWER =	19.3315

FILTER # = 8	FREQUENCY = 3.140
TOTAL POWER =	68.6336

FILTER # = 9	FREQUENCY = 3.500
TOTAL POWER =	248.6265

FILTER # = 10	FREQUENCY = 3.970
TOTAL POWER =	307.3279

FILTER # = 11	FREQUENCY = 4.470
TOTAL POWER =	97.4597

FILTER # = 12	FREQUENCY = 5.030
TOTAL POWER =	122.1950

FILTER # = 13	FREQUENCY = 5.650
TOTAL POWER =	72.0854

FILTER # = 14	FREQUENCY = 6.360
TOTAL POWER =	7.0922

FILTER # = 15	FREQUENCY = 7.150
TOTAL POWER =	16.0353

FILTER # = 16	FREQUENCY = 8.050
TOTAL POWER =	22.4882

FILTER #= 17	FREQUENCY =	9.050			
TOTAL POWER=	2.3833				
FILTER #= 18	FREQUENCY =	10.190			
TOTAL POWER=	56.5992				
FILTER #= 19	FREQUENCY =	11.460			
TOTAL POWER=	28.1444				
FILTER #= 20	FREQUENCY =	12.890			
TOTAL POWER=	43.7750				
CORE USAGE	OBJECT CODE=	5268 BYTES,ARRAY AREA=	2000 BYTES,TOTAL AREA AVAILABLE=	49486	BYTES
DIAGNOSTICS	NUMBER OF ERRORS=	0,	NUMBER OF WARNINGS=	0,	NUMBER OF EXTENSIONS=
COMPILE TIME=	3.37 SEC,EXECUTION TIME=	2.94 SEC,	KATFIV - VERSION 1	MARCH 1971	DATE= 72/095

SMOOTHED PINK-R SPECTRUM

DELTA T = 0.0385 ZETA = 0.6546 FREQUENCY SCALE = 10.0000 (s)

THE COMPUTED FREQUENCIES ARE.....

BASE = 1.300

NYQUIST = 13.000

TABLE OF FILTER CENTER FREQUENCIES

COUNT	CENTER FREQUENCY	BANDWIDTH	3 DB CROSS 1/2 PT.
1	1.376657	0.1019	1.4571
2	1.548439	0.1621	1.6623
3	1.741909	0.2048	1.8475
4	1.959553	0.2304	2.0764
5	2.204390	0.2592	2.3381
6	2.479818	0.2916	2.6302
7	2.789660	0.3281	2.9536
8	3.138214	0.3691	3.3203
9	3.530322	0.4152	3.7444
10	3.971420	0.4670	4.2122
11	4.467631	0.5234	4.7255
12	5.025842	0.5910	5.3305
13	5.653798	0.6649	5.9966
14	6.360215	0.7480	6.7439
15	7.154896	0.8414	7.5827
16	8.049868	0.9465	8.5369
17	9.054539	1.0648	9.6036
18	10.195860	1.1979	10.8035
19	11.458540	1.3475	12.1533
20	12.890230	1.5159	13.6711

INPUT SAMPLED DATA: P1(m)

1.83	3.62	1.49	-2.54	-2.41	-0.84	-0.08	2.27	0.45	-0.67
-1.05	-0.96	0.98	-1.07	0.24	1.04	-1.85	0.19	-2.67	-0.34
0.07	1.43	0.24	0.55	-0.64	0.56				

FILTER # = 1	FREQUENCY =	1.376
TOTAL POWER =	10.7119	
FILTER # = 2	FREQUENCY =	1.548
TOTAL POWER =	4.7482	
FILTER # = 3	FREQUENCY =	1.742
TOTAL POWER =	13.9064	
FILTER # = 4	FREQUENCY =	1.960
TOTAL POWER =	37.5840	
FILTER # = 5	FREQUENCY =	2.204
TOTAL POWER =	58.1155	
FILTER # = 6	FREQUENCY =	2.480
TOTAL POWER =	52.4283	

FILTER #= 7	TOTAL POWER=	FREQUENCY =	2.79C
		33.6061	
FILTER #= 8	TOTAL POWER=	FREQUENCY =	3.138
		60.7156	
FILTER #= 9	TOTAL POWER=	FREQUENCY =	3.53C
		140.1672	
FILTER #= 10	TOTAL POWER=	FREQUENCY =	3.971
		156.6906	
FILTER #= 11	TOTAL POWER=	FREQUENCY =	4.468
		90.0711	
FILTER #= 12	TOTAL POWER=	FREQUENCY =	5.026
		71.8861	
FILTER #= 13	TOTAL POWER=	FREQUENCY =	5.654
		35.7446	
FILTER #= 14	TOTAL POWER=	FREQUENCY =	6.360
		10.8121	
FILTER #= 15	TOTAL POWER=	FREQUENCY =	7.155
		12.1541	
FILTER #= 16	TOTAL POWER=	FREQUENCY =	8.049
		8.7351	
FILTER #= 17	TOTAL POWER=	FREQUENCY =	9.055
		2.1489	
FILTER #= 18	TOTAL POWER=	FREQUENCY =	10.186
		1.7850	
FILTER #= 19	TOTAL POWER=	FREQUENCY =	11.459
		0.5198	
FILTER #= 20	TOTAL POWER=	FREQUENCY =	12.89C
		0.0222	

CORE USAGE OBJECT CODE= 5268 BYTES,ARRAY AREA= 2000 BYTES,TOTAL AREA AVAILABLE= 49498 BYTES

DIAGNOSTICS NUMBER OF ERRORS= 0, NUMBER OF WARNINGS= 0, NUMBER OF EXTENSIONS= 0
 COMPILE TIME= 3.39 SEC,EXECUTION TIME= 3.17 SEC, KATFIV - VERSION 1 LEVEL 3 MARCH 1971 DATE= 72/095

REFERENCES

1. N. Ahmed, K. R. Rao and S. K. Tjoe, "Time-varying Fourier Transform", *Electronics Letters*, Vol. 7, No. 18, 9th September 1971, pp. 535-536.
2. C. R. Arnold, "Spectral Estimation for Transient Waveforms", *IEEE Trans. Audio Electroacoust.*, Vol. AU-18, pp. 248-257, Sept. 1970.
3. N. Ahmed and K. R. Rao, "Principles of Basic Digital Signal Processing Techniques", manuscript (Kansas State University).
4. N. Ahmed, T. Natarajan, K. R. Rao and R. B. Schultz, "A Time-varying Power Spectrum", *IEEE Trans. Audio Electroacoust.*, Vol. AU-19, pp. 327-328, Dec. 1971.

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SPECTRAL ANALYSIS OF APERIODIC DIGITAL SIGNALS

by

T. NATARAJAN

B. E., 1970, Annamalai University, Tamilnadu, India

AN ABSTRACT OF A MASTER'S REPORT

submitted in partial fulfillment of the

requirements for the degree

MASTER OF SCIENCE

Department of Electrical Engineering

KANSAS STATE UNIVERSITY
Manhattan, Kansas

1972

ABSTRACT

This report can be divided into two parts. First, the time-varying Fourier transform which was recently introduced for noise-free discrete signals is extended to the case when noise is present. Next, a study of Arnold's on-line computational algorithm is presented.

It is demonstrated that Arnold's algorithm can be effectively used for the signal representation of noisy transient waveforms, prior to their classification. In such cases since the transients are usually well below the noise level, their epoch and duration are not known. Therefore, standard techniques available such as fast Fourier transform fail to yield adequate signal representation of the transients.

Again, it is shown that the time-varying Fourier transform can be used for the effective estimation of Fourier power and phase spectra of transients in the presence of noise, with any desired frequency resolution. It is also demonstrated that the spectral estimates so obtained are superior to those obtained by standard smoothing techniques.