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The application of an adaptive least squares lattice filter in the detection of heartbeat occurrences in measurements from a remote microwave vital life signs monitor

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THE APPLICATION OF AN ADAPTIVE LEAST SQUARES LATTICE FILTER IN THE DETECTION OF HEARTBEAT OCCURRENCES IN MEASUREMENTS FROM A REMOTE MICROWAVE VITAL LIFE SIGNS MONITOR

By

Patricia Ann Mahoney

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ABSTRACT

THE APPLICATION OF AN ADAPTIVE LEAST SQUARES LATTICE FILTER IN THE DETECTION OF HEARTBEAT OCCURRENCES IN MEASUREMENTS FROM A REMOTE MICROWAVE VITAL LIFE SIGNS MONITOR

By

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A portable remote microwave vital life signs monitor has been built. Heart rate is estimated by detecting Doppler shifts of a microwave signal that illuminates the chest wall of a human. A method of detecting heartbeats is based on modeling the microwave heartbeat signal as the output of an all-pole filter that has been excited by a pseudo-periodic impulse train. An adaptive least squares lattice filter is used.

The use of this detection method for a modified version of the monitor is verified in this research. Estimates of the coefficients of the all-pole filter are found. The detection method works well for only a limited set of operating conditions of the modified monitor. The results of the verification process suggest an alternative heartbeat detection method could be based on the detection of changes in the statistics of the microwave heartbeat signal.

ACKNOWLEDGMENTS

The author wishes to thank Betsy Mates-Needham and Michael Francois for all of their help. She is especially grateful to Betsy Mates-Needham for her help in the development of the computer program in Appendix J.

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INTRODUCTION

There is an interest in developing a noninvasive vital life signs detector that will be used by medical personnel working in hazardous environments. One requirement of the instrument is that it is able to measure a human's heart rate at distances up to 6 inches from the body and through protective clothing. A portable low energy microwave device has been developed to measure heart rate by detecting pertubations of the chest wall due to the heart beating. The device operates by illuminating the chest wall with a pulsed X-band microwave signal. Relative motion between the device and the chest wall is detected by Doppler shifts in the reflected microwave signal. Under realistic operating conditions, breathing, body, and background movements obscure the heartbeat signal. The current challenge is to develop a real-time signal processing technique that will extract heartbeat information from the microwave returns.

Past efforts to measure heart rate from the microwave signal have used various time and frequency domain detection methods (Byrne, Flynn, Zapp, & Siegel, 1986; Byrne & Siegel, 1985; Byrne, Zapp, Flynn, & Siegel, 1985; Hoshal, Ivkovich, Siegel, & Zapp, 1984; Hoshal & Siegel, 1985; Hoshal, Siegel, & Zapp, 1984; Lin, Kiernicki, Kiernicki, & Wollschlaeger, 1979; Popovic, Chan, & Lin, 1984). The heart rate estimation techniques can be classified into two groups, techniques that rely the periodic nature of the heartbeat and techniques that attempt to identify individual heartbeats in order to estimate heart rate. Detection techniques that rely on the periodic nature of the heartbeat signal have had limited success because heartbeat occurrences are pseudo-periodic. Time periods between heartbeats are not always constant. Autocorrelation is an example of such a technique. Averaging techniques such as autocorrelation also perform poorly in tracking instantaneous changes in the heart rate.

Under ideal conditions, individual heartbeats can be easily identified in the microwave heartbeat signal. A microwave heartbeat signal looks somewhat like an electrocardiogram (EKG). The occurrence of a heartbeat in the microwave signal appears to be impulsive in nature. Peak detection can be used to locate individual heartbeats in microwave heartbeat signals recorded under ideal operating conditions. Peak detection fails under more realistic operating conditions because the heartbeat signal is obscured by clutter due to breathing and background movement. The search for a "universal" heartbeat signature in the microwave signal has been unsuccessful (M. Siegel, personal communication, 1988). The signature of the heartbeat changes with orientation and distance of the microwave device with respect to the chest wall. The signature can vary from person to person and from heartbeat to heartbeat (Byrne & Siegel, 1985).

The extraction of an impulsive signal from a processes is also a problem in geophysics and speech analysis. Adaptive linear prediction is a useful technique in recovering impulse occurrences from seismic traces and speech processes (Friedlander, 1982b; Lee & Morf, 1980; Makhoul, 1975). Because of the similarity between the impulsive nature of heartbeat occurrences in the microwave signal and pitch pulses in speech processes, Byrne and Siegel (1985) adopted a microwave heartbeat signal model and heartbeat detection technique that are similar to the speech process model and pitch pulse detector presented in Lee and Morf (1980). The detection methods are based on adaptive linear prediction. The particular predictor used by Byrne and Siegel was an adaptive least squares lattice filter, a computationally efficient implementation of an adaptive least squares linear predictor. Byrne and Siegel showed that the adaptive least squares lattice filter worked well in extracting heartbeats from microwave signals recorded under ideal and adverse operating conditions.

Byrne and Siegel (1985) worked with the Michigan State University Biomedical Signal Processing Laboratory vital life signs monitor. Other work related to this monitor was done by

Byrne, Flynn, Zapp, and Siegel (1986), Byrne, Zapp, Flynn, and Siegel (1985), Hoshal, Ivkovich, Siegel, and Zapp (1984), Hoshal and Siegel (1986) and Hoshal, Siegel, and Zapp (1984). A comprehensive history of the development of a heart rate estimation technique for the Michigan State University vital life signs monitor is given in Appendix K. A number of modification have been made to the design of the vital life signs monitor since the Byrne and Siegel (1985) study. The modifications were made to improve the safety of the device, minimize power consumption, increase the monitor's dynamic range and sensitivity, and filter out signal components related to breathing. The standard position of the monitor during the recording of test data has also changed. The new monitor position provides data that will test the heart rate estimation techniques under development more extensively.

The microwave signals recorded from the modified microwave unit appear to be very different from the microwave signals that Byrne and Siegel (1985) used during the development of their heartbeat detector. The purpose of this research is to verify that the Byrne and Siegel model and the use of the Byrne and Siegel heartbeat detector are valid for the microwave heartbeat signals recorded from the modified monitor. The adaptive least squares lattice filter used in the Byrne and Siegel heartbeat detector has parameters that must be defined before the detection technique can be used. Byrne and Siegel did not give a systematic method of selecting values for the lattice filter user defined parameters. Therefore, the bulk of this research effort is involved in the selection of user defined lattice filter parameter values. A byproduct of this verification process is an alternative heartbeat detection method based on the detection of changes in the statistics of the microwave heartbeat signal.

RESEARCH OBJECTIVES

The primary objective of this thesis research is to verify that the Byrne and Siegel (1985) model and heartbeat detection method are valid for microwave heartbeat signals recorded from the modified vital life signs monitor. Byrne and Siegel models the microwave heartbeat signal as the output of an all-pole filter that is excited by a process consisting of a pseudo-periodic impulse train added to band-limited white noise. Equation 1 is the transfer function of the all pole filter.

$$H_{all-pole\ filter}(z) = \left[\frac{1}{1 + \sum_{i=1}^{M} A_i z^{-i}} \right], \quad (1)$$

where M is the order of the filter and A_i is a coefficient of the filter. The impulse train represents the original heartbeat signal. The all-pole filter represents the system the heartbeat signal passes through. Adaptive linear prediction can be used to deconvolve the output of an all-pole filter that has been excited by a white process or an impulse train (Friedlander, 1981; Friedlander, 1982b; Lee & Morf, 1980; Makhoul, 1975). The excitation process is recoverable from the prediction error sequence. Adaptive linear prediction can also be used to identify the coefficients of the all-pole filter. Assuming that adaptive linear prediction will inverse the operation of an all-pole filter on a process consisting of an impulse train added to white noise, Byrne and Siegel applys adaptive linear prediction to the microwave heartbeat signal in order to recover the heartbeat occurrences from the linear prediction residuals. The heartbeat signal should appear as a sequence of large prediction errors.

The Byrne and Siegel (1985) model is very similar to the autoregressive (AR) process model. For the benefit of the unfamiliar reader, Appendix L gives a review of the AR model and the use of linear prediction in the identification of AR model parameters. The adoption of the Byrne and Siegel model for the microwave heartbeat signal was motivated by the speech process model used by Lee and Morf (1980) in their development of a pitch pulse detector. Appendix M gives a simplified illustration of the use of linear prediction in the analysis of speech processes for the benefit of the unfamiliar reader.

Byrne and Siegel (1985) uses an adaptive least squares lattice filter as the linear predictor in their heartbeat detection technique. The lattice filter is a normalized version of the the least squares lattice filter used by Lee and Morf (1980). The lattice filter parameter update algorithm is recursive.

A lattice filter parameter called the likelihood variable aids in the identification of large prediction errors associated with heartbeat occurrences. The likelihood variable is related to the log-likelihood function of the process that is input to the lattice filter. The likelihood variable is a measure of the likelihood that successive data samples will come from the same Gaussian distribution (Lee & Morf, 1980). The likelihood variable is a good detection statistic of the "unexpectedness" of the most recent input data points (Friedlander, 1982a). A function of the likelihood variable is used in the lattice filter parameter update algorithm. The likelihood variable function enables the lattice filter to quickly adapt to unexpected data (Lee & Morf, 1980). Byrne and Siegel found that the sequence formed by subtracting the value of the likelihood variable for the previous time step from the current likelihood variable value could be used to isolate the large prediction errors that are associated with heartbeat occurrences. The likelihood variable difference sequence is used to mask out prediction errors that are not associated with heartbeat occurrences.

The first step of the Byrne and Siegel (1985) heartbeat detection procedure is to pass the microwave heartbeat signal through the lattice filter. The likelihood variable difference sequence is formed. The prediction error sequence and the likelihood variable difference sequence are multiplied together. The result is a sequence of isolated large prediction errors that represent possible heartbeats. The primary objective of this research is to verify that heartbeats in the microwave heartbeat signals from the modified monitor can be extracted with the Byrne and Siegel procedure. The first step of the verification process will be to apply the lattice filter to microwave heartbeat signals recorded from the modified monitor and observe the behavior of the prediction error sequence and the likelihood variable sequence.

Byrne and Siegel (1985) did not investigate the behavior of the configuration of the all-pole filter in their microwave heartbeat signal model. The behavior of the all-pole filter configuration might contain information that is useful in the development of a heart rate estimation technique. The second objective of this research is to estimate the coefficients of the all-pole filter and observe how they behave in time.

VERIFICATION METHOD AND THE METHOD USED TO ESTIMATE THE ALL-POLE FILTER COEFFICIENTS

The Lattice Filter Parameter Update Algorithm

The Unnormalized Pre-Windowed Least Squares Lattice Filter from Friedlander (1982a, pp. 842-844) was used in the verification of the Byrne and Siegel (1985) heartbeat detection method for the microwave heartbeat signals recorded from the modified monitor. The prediction error and the likelihood variable are directly available from the lattice filter parameter update algorithm. The lattice filter parameter update algorithm and a Fortran implementation of the lattice filter are given in Appendix E and Appendix G, respectively. For those who are unfamiliar with least squares linear prediction and the lattice form, see Appendix L and Appendix N. The all-pole filter coefficient estimates were obtained from the lattice filter parameters through an algorithm given by Friedlander (1982a, pp. 845). The algorithm used to estimate the all-pole filter coefficients is given in Appendix F. Appendix H gives a Fortran implementation of the algorithm used to estimate the all-pole filter coefficients.

The Data Base of Files Recorded from the Modified Monitor

The verification process was facilitated by the formation of a data base of microwave signals recorded for various operating conditions of the modified microwave vital life signs monitor.

Samples of files from the data base are given in Appendix A. There are 1024 data samples in each data file. The sampling rate was 64 samples per second. Microwave signals were recorded for two kinds of reflective surfaces, human subjects and inanimate objects. The inanimate objects consisted of a wool surface, a metal surface, and an open room.

In the experiments reported in this research, there were four human subjects. For each human subject five microwave signals were recorded. Four of the five signals resulted from reflecting a microwave signal off the chest wall of the subject. The fifth recorded signal resulted from reflecting the microwave signal off one of the subject's legs. Each subject was rested and holding his/her breath for the first chest wall file. The subjects were resting and breathing normally for the second chest wall file. In the third file, the subjects had been exercising and held their breath. The subjects were exercised and breathing for the fourth chest wall file.

The monitor had the same position with respect to the subject for each chest wall file. The subjects were seated. The monitor was pointed just left of center of the chest wall. Studies previous to this research showed that the strongest heartbeat signals can be found in microwave signals recorded with the monitor positioned left of center of the chest wall (M. Siegel, personal communication, 1988). The monitor was place about 6 inches from the subject. The subjects were wearing street clothes.

Heartbeat reference signals were obtained from an in-house designed unit that measures body surface potential between the hands of a human subject. The output of the device resembles an EKG signal. A hand potential reference heartbeat signal was simultaneously recorded for each chest wall file.

A microwave signal reflected from the bare calf of a leg of each subject was recorded. The monitor was positioned 6 inches from the leg. A hand potential reference heartbeat signal was simultaneously recorded. Movement detected in the returns of the microwave signal from the leg due to the heart beating is expected to be insignificant.

The data base includes three files where the microwave signals were reflected from the inanimate objects. One microwave file was recorded for a microwave signal reflected from a wool surface placed 6 inches from the monitor. The second file resulted from microwave reflections from a flat metal surface placed 6 inches from the monitor. The third file is a record of returns from a microwave signal sent into an open room.

The Selection of Lattice Order

The proper order of the lattice filter must be chosen before the verification of the Byrne and Siegel (1985) model and heartbeat detection method for the modified monitor can proceed. The order of the all-pole filter in the Byrne and Siegel model will be the same as the proper order of the lattice filter. The method used to determine the proper order of the lattice filter is based on the optimization criterion of least squares linear prediction. In linear prediction the current value of a process is estimated by a linear combination of past values of the process. The coefficients in the linear combination are chosen such that the sum of the squared prediction errors is minimized. The proper order of the linear predictor is the number of past data elements in the linear combination. If the order of the least squares linear predictor is greater than the order of the process, the linear predictor is using past data in its prediction of the current data point that the current data point is not dependent on. The excess past process elements should not make a contribution to the prediction of the current data item. The weight the linear predictor assigns to the excess process elements should be close to zero. If the excess process elements make only a small contribution to the prediction of the current process element, then the sum of the squared error should not significantly change with an increase in linear prediction order beyond the order of the process (Chandra & Lin, 1974). The order of the microwave heartbeat signals was determined by processing the signals with a high order lattice filter and then calculating the mean of the sum of the squared prediction errors for each lower order section of the lattice filter. The order of the process was chosen to be the order at which the mean of the sum of the squared prediction errors, or the variance of the prediction errors, began to level off for increasing lattice filter order.

A preliminary study was done in order to establish a range for the order of the microwave signals in the data base. Data files recorded from the microwave signal being reflected from a human chest wall, a human leg and the inanimate objects were processed through a lattice filter of order 8. The exponential weighting factor, a parameter of the lattice to be explained in the next section, was arbitrarily set to 0.95. The variance of the prediction error leveled off at order 4 for each data file.

In all subsequent analyses of files from the data base, a lattice filter of order 6 was used. The exponential weighting factor was set to 0.99 for reasons given in the next section. The variance of the prediction errors for order 1 through 6 were recorded for each file in the data base. The results are tabulated in Appendix B. The results in Appendix B are the same as the results of the preliminary study. The variance of the sum of the squared prediction errors for each file in the data base appears to level off at order 4.

The Selection of a Value for the Exponential Weighting Factor, λ

A second parameter of the lattice filter that needs to be defined before the lattice filter can be used is the exponential weighting factor, λ. The exponential weighting factor determines the configuration of exponential window that weights the past data used in the estimation of the statistics of the signal being processed by the lattice filter. As the value of λ increased, the length of the exponential window increases. A study of λ's effect on the lattice filter's processing of microwave heartbeat signals was made in order to chose a value for λ.

A group of chest wall microwave signals from the data base were processed through the lattice filter with λ set at various values. λ was set to values ranging from 0.99 to 0.85. A 4th order lattice was used. The behavior of the output and parameters of the lattice filter was observed for each file. Three consistent behavior patterns were observed. The behavior patterns occurred in the estimated coefficients of the all-pole filter, the likelihood variable, and the prediction error sequence.

The value of the all-pole filter parameters were updated for every new data element of the file being processed. Figure 1 through Figure 4 illustrate how the four all-pole filter coefficients vary in time for $\lambda = 0.99$, $\lambda = 0.95$, and $\lambda = 0.90$. For $\lambda = 0.99$, the plots of the all-pole filter coefficients are smooth. As λ decreases in value, the plots of the coefficients show large variations.

Figure 5 shows how the likelihood variable behaves for $\lambda = 0.99$, $\lambda = 0.95$, and $\lambda = 0.90$. As λ decreases in value the variation of the likelihood variable increases. In most of the chest wall files studied, a rise and fall of the likelihood variable can be correlated with a heartbeat occurrence from the hand potential heartbeat reference signal. Although the behavior of the likelihood variable reported in Byrne and Siegel (1985) is similar, the rise and fall of the likelihood variable associated with the occurrence of a heartbeat are faster in the Byrne and Siegel study. The rise and fall of the likelihood variable in this research appears to be more like a hump.

The behavior of the prediction error sequences for decreasing values of λ was opposite the behavior of the all-pole filter coefficients and the likelihood variable. As λ decreases, the amplitude of the largest prediction errors seem to decrease. The variation of the prediction error for decreasing values of λ is not as pronounced as the variations observed in the all-pole filter coefficients and the likelihood variable. The variance in the prediction error for different values

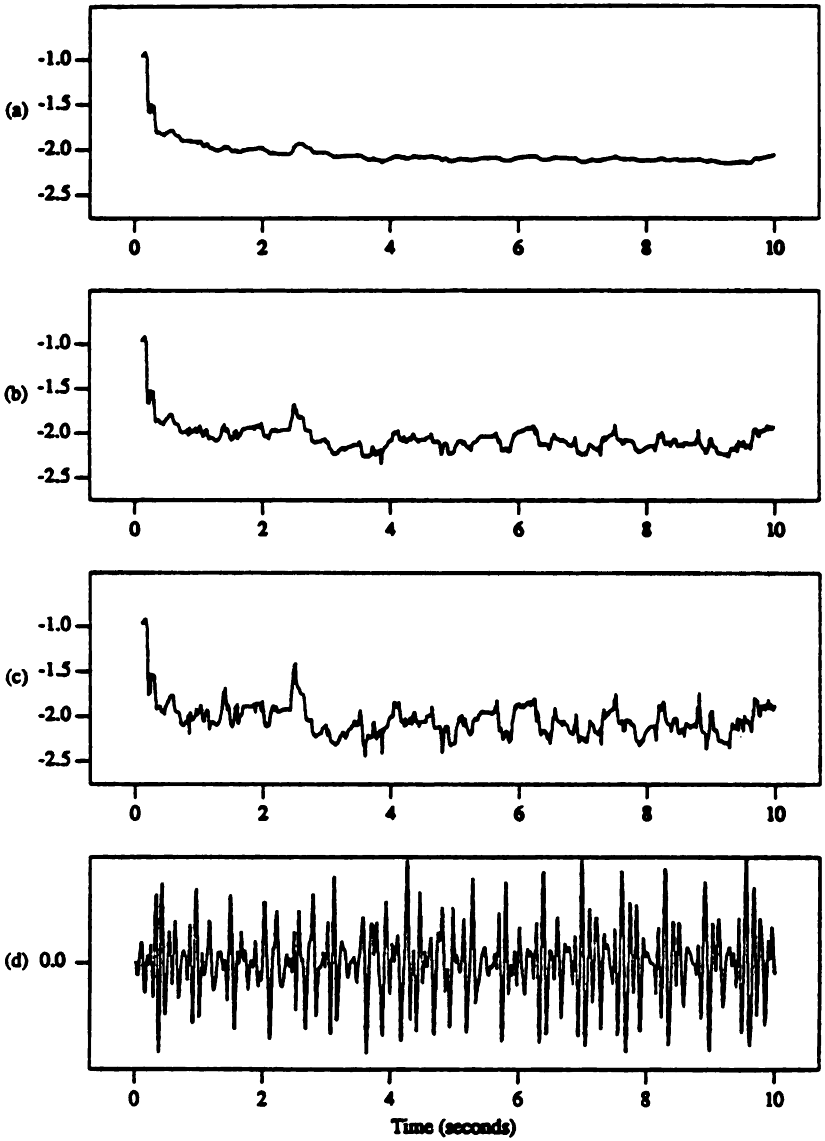


Figure 1. AR model all-pole filter coefficient A_1 for a chest wall microwave signal. (a) A_1 for λ=0.99. (b) A_1 for λ=0.95. (c) A_1 for λ=0.90. (d) chest wall microwave signal.

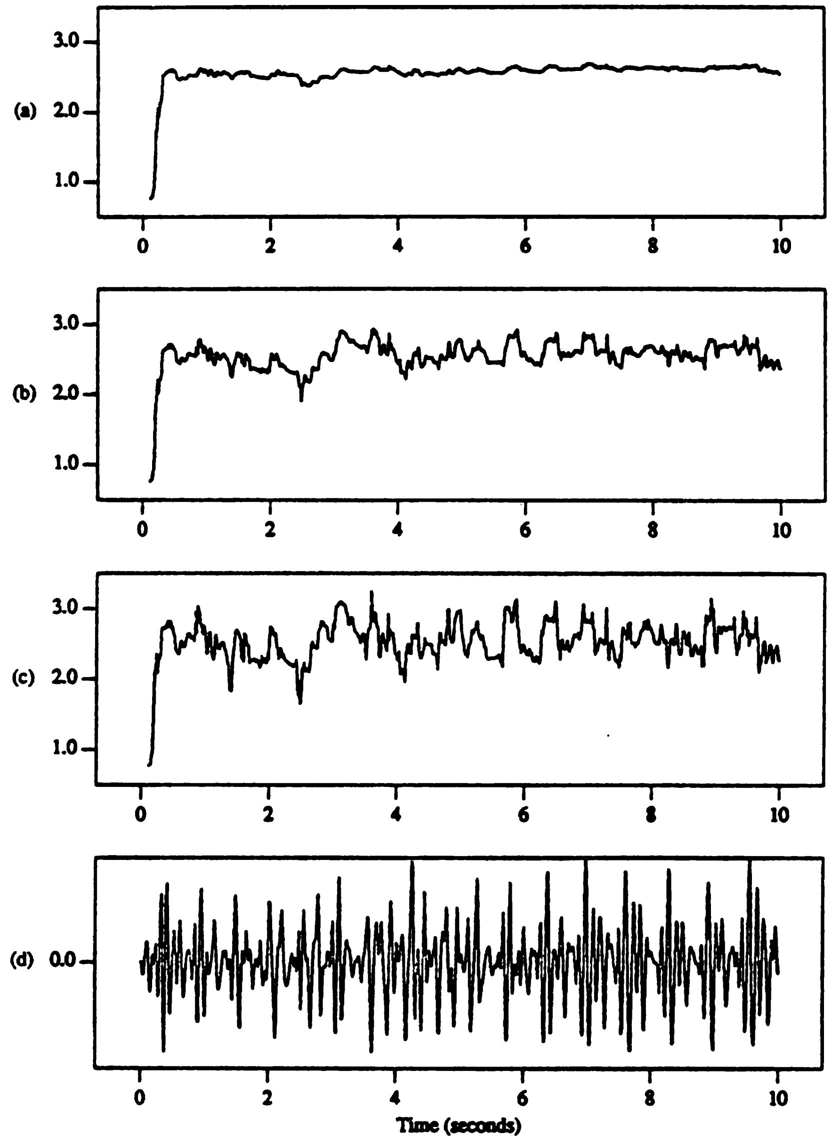


Figure 2. AR model all-pole filter coefficient A_2 for a chest wall microwave signal. (a) A_2 for λ=0.99. (b) A_2 for λ=0.95. (c) A_2 for λ=0.90. (c) chest wall microwave signal.

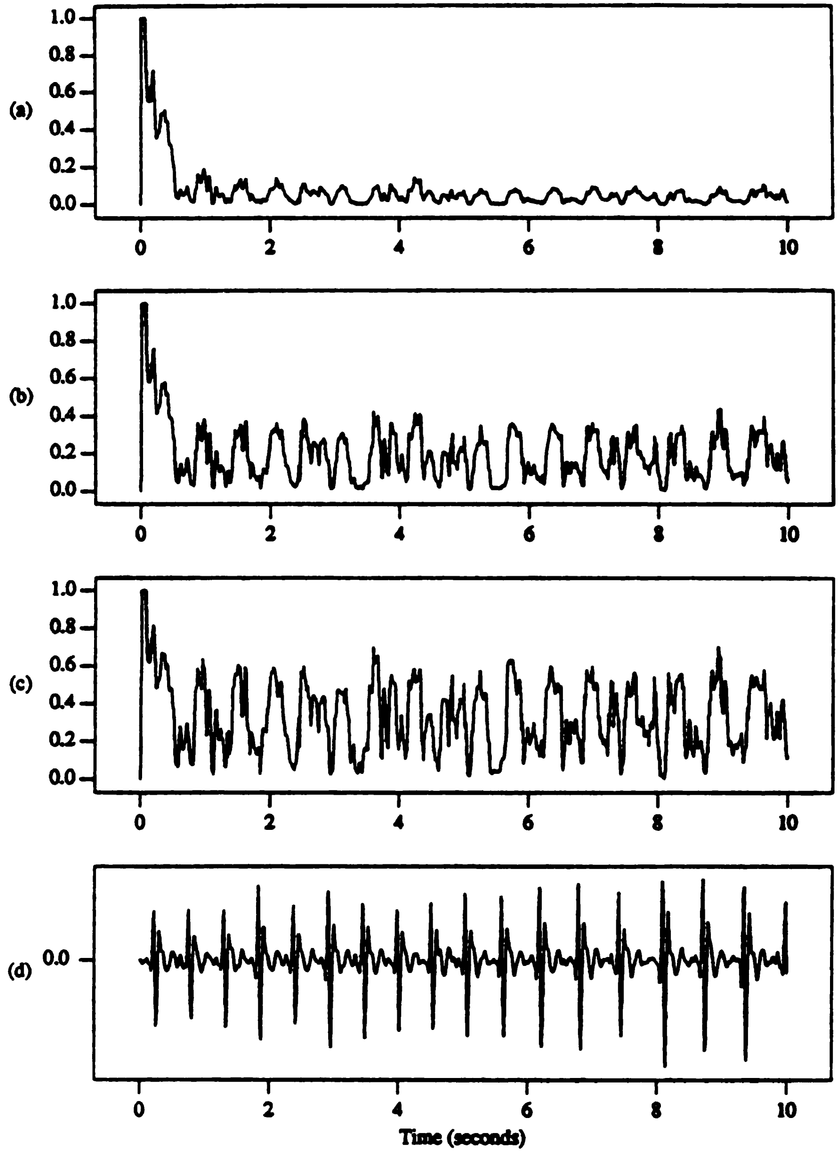


Figure 5. The effect of λ on the likelihood variable. (a) likelihood variable with λ=0.99. (b) likelihood variable with λ=0.95. (c) likelihood variable with λ=0.90. (d) hand potential heart-beat signal.

of λ is greater for some files than it is for others. Figure 6 and Figure 7 show the error sequence for two different files from the data base filtered with $\lambda = 0.99$, $\lambda = 0.95$, and $\lambda = 0.90$. The variance is greater for the prediction error sequence in Figure 6 that it is in Figure 7.

The behaviors of the all-pole filter coefficients, the likelihood variable and the prediction error sequence can be related to each other by considering the length of the exponential weighting window of the lattice filter. As λ increases, the length of the exponential window increases. For larger values of λ, the lattice filter's memory of the process it is trying to predict is longer. More past values are used by the lattice filter to estimate the statistics of the process.

The likelihood variable can be used as an indicator of the event that the most recent data points received by the lattice filter are outliers from the Gaussian distribution of the data that the filter has in its memory (Lee & Morf, 1980). As λ decreases, the variance of the likelihood variable increases for the microwave heartbeat signals. Generally, the periods during which the likelihood variable rises and falls correlate with occurrences of heartbeats. The microwave heartbeat signal appears to be different in character for periods that correlate with the occurrence of heartbeats. If the length of the memory of the lattice filter is shorter than the time between heartbeats, then the occurrence of a microwave heartbeat may appear to be a far outlier from the distribution of the data points that just preceded it. Under these conditions, the value of the likelihood variable should rise. If the memory of the lattice filter covers the occurrence of several heartbeats, the occurrence of a new heartbeat may not appear to be such a distant outlier. The value of the likelihood variable would vary less for a lattice filter with a long memory than for a lattice filter with a short memory.

The behavior of the likelihood variable directly affects the estimation of the lattice filter parameters used to calculate the all-pole filter coefficients. A function of the likelihood variable is used as a gain in the update algorithm for the lattice filter parameters. The gain enables the lattice filter to quickly adapt to changes in the process being predicted. If the likelihood variable is

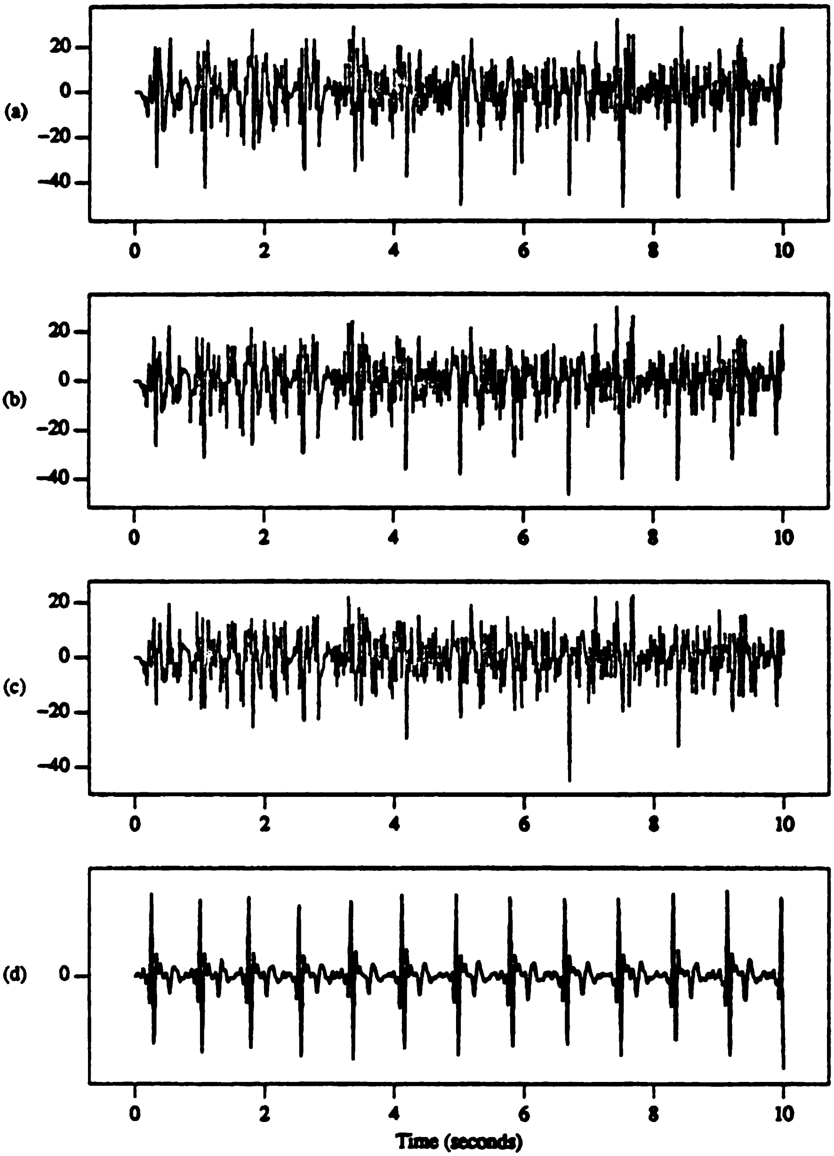


Figure 6. The effect of λ on the prediction error sequence, example 1. (a) error sequence with $\lambda=0.99$. (b) error sequence with $\lambda=0.95$. (c) error sequence with $\lambda=0.90$. (d) hand potential reference.

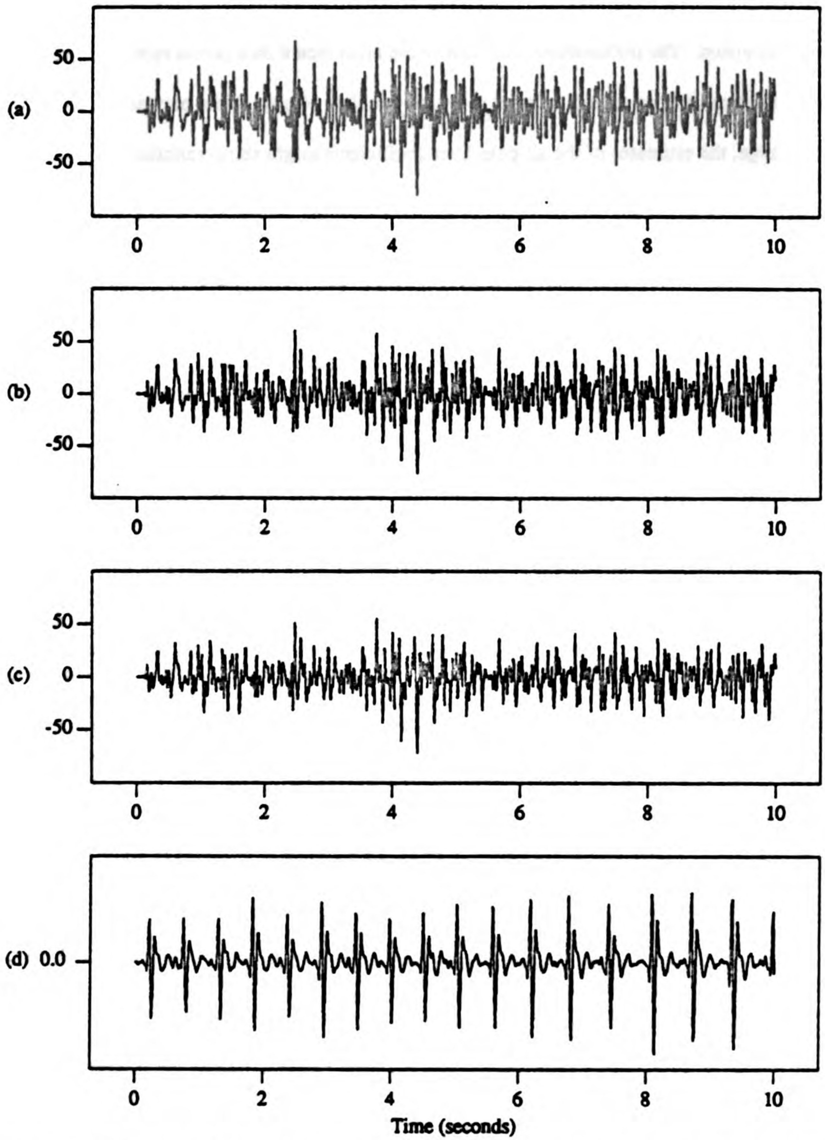


Figure 7. The effect of λ on the prediction error sequence, example 2. (a) error sequence with λ=0.99. (b) error sequence with λ=0.95. (c) error sequence with λ=0.90. (d) hand potential reference.

large, then the lattice filter responds by altering its parameters to minimize the sum of the squared prediction errors. The information contained in the most recent data points received by the lattice filter will be considered to be the target to which the filter adapts. If the parameters of the lattice filter change, the estimates of the all-pole filter coefficients might show variations.

The variations in the prediction error sequences can be related to the length of the memory of the lattice filter. When the memory of the lattice filter is short, the data the lattice filter is trying to adapt to is localized. The likelihood variable is more sensitive to changes in the data the lattice filter receives. If the likelihood variable is more sensitive to changes, then the lattice filter is better able to track short term changes in the microwave signal such as microwave reflections during the occurrence of a heartbeat. Consequently, the lattice filter may be better able to minimize the sum of the squared prediction errors. This would explain why the amplitudes of the largest prediction errors decrease for decreasing lattice filter exponential window length.

The value of λ chosen for the verification of the Byrne and Siegel (1985) model and heartbeat detection method was $\lambda = 0.99$. Long lattice filter memory was chosen because the large prediction errors associated with heartbeats in the hand potential reference signal were more pronounced. The all-pole coefficient sequences are smooth for $\lambda = 0.99$.

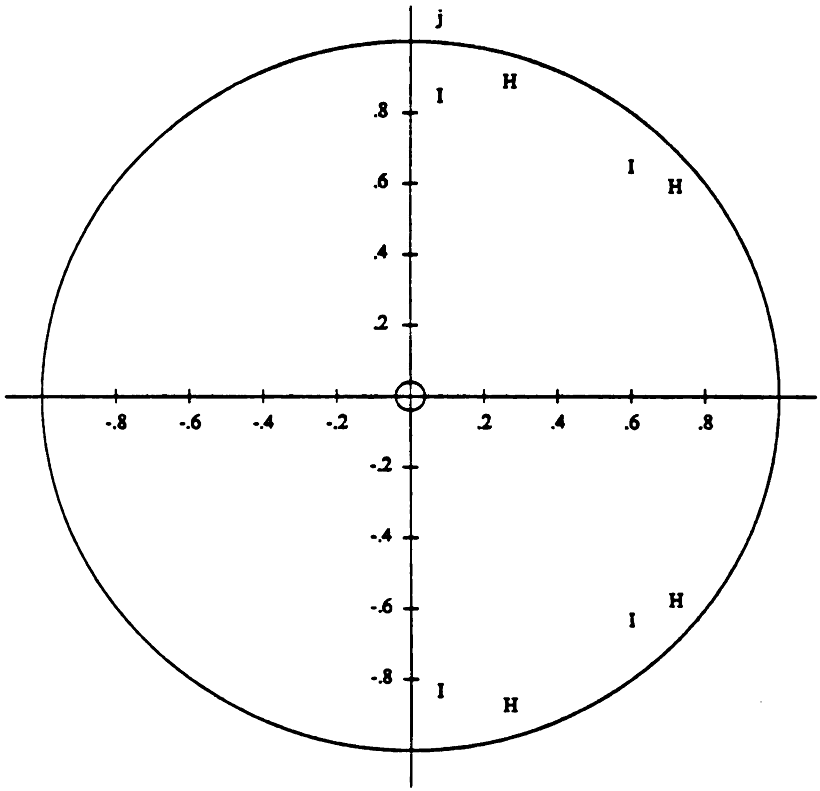
RESULTS

The Byrne and Siegel Model All-Pole Filter Coefficients

Estimates of the all-pole filter coefficients were found for each file in the data base. The all-pole filter coefficient estimates were updated for each point in a file. A mean value of each coefficient for each data base file was found from a sample of consecutive estimates of the coefficients. Each sample consisted of 600 points starting at point 200 or 3 seconds into the coefficient file. The purpose of the delay in the start of the sample was to ensure that the lattice filter parameters had converged. Appendix C is a tabulation of the all-pole filter coefficient sample averages for each file in the data base.

The all-pole filter coefficients of files for microwaves reflected from the human subjects are close in value. The all-pole filter coefficients of files for microwaves reflected from inanimate objects are close in value. The mean of the coefficients for the human subject files and the mean of the inanimate object coefficients are given in Appendix C. The coefficients for the inanimate object files are lower in value than the coefficients for the human subject files.

In order to determine if the difference between the inanimate object file all-pole filter configuration and the human subject file all-pole filter configuration is significant, pole-zero plots were made for the transfer functions of the all-pole filters for both file types. The pole-zero plots are in Figure 8. The four poles of each all-pole filter appear as two conjugate pairs in the pole-zero plot. The plot shows that the poles of the different file types are close. Figure 9a and Figure 9b are plots of the amplitude responses of the different file type all-pole filters. Although the



$$H_{\text{Human Subject}}(z) = \frac{z^4}{z^4 - 1.984z^3 + 2.485z^2 - 1.684z + .7273}$$

$$H_{\text{Inanimate Object}}(z) = \frac{z^4}{z^4 - 1.356z^3 + 1.680z^2 - 1.013z + .5994}$$

Figure 8. Pole-zero plots of the AR model all-pole filters for the human subject files and the inanimate object files. H - Human subject AR model all-pole filter poles. I - Inanimate object AR model all-pole filter poles.

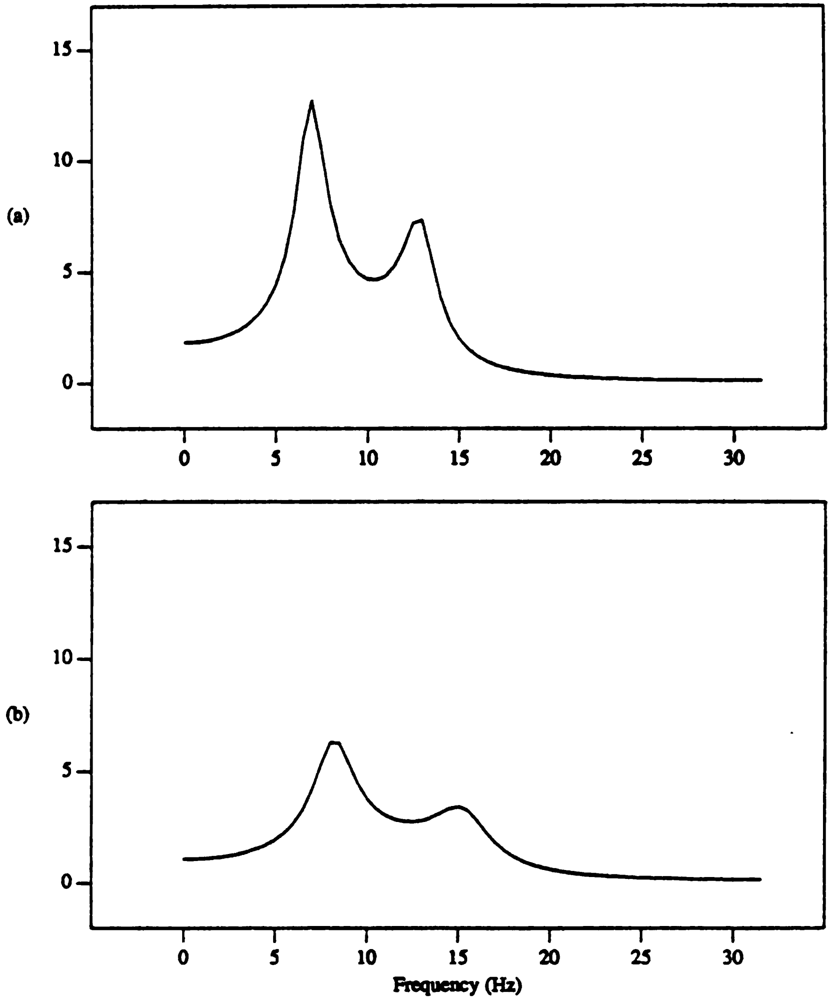


Figure 9. Amplitude frequency response AR model all-pole filter for the human subject files and the inanimate object files. (a) frequency response for the human subject files. (b) frequency response fo the inanimate object files.

resonance peaks for the all-pole filter for the human subject file are greater in magnitude than the resonance peaks for the all-pole filter of the inanimate object files, the resonance peaks are at approximately the same frequencies

Recovery of the Heartbeat Signal from the Microwave Heartbeat Signal

The primary objective of this research was to verify that the Byrne and Siegel (1985) model and heartbeat detection technique are valid for the microwave heartbeat signals recorded from the modified monitor. If the Byrne and Siegel model is valid for the modified monitor microwave heartbeat signals and linear prediction will inverse the operation of an all-pole filter on a process consisting of an impulse train added to white noise, then the prediction errors of the lattice filter should consist of an impulse train added to white noise. The impulse train should correlate to the occurrences of heartbeats in the hand potential reference signal.

Only a few chest wall files had prediction error sequences that resembled an impulse train added to white noise. These files were recorded under ideal conditions. The human subject was at rest and holding her/his breath. There was little movement of the chest wall due to breathing or the body moving. Figure 10 shows the original microwave heartbeat signal and the prediction error sequence for a chest wall file where the model is well fitted.

Heartbeat occurrences in chest wall files recorded under more realistic operating conditions are not easily detectable from the prediction error sequences. For files where the subjects were breathing, the prediction errors at locations of heartbeats were not distinguishable from other prediction errors. Figure 11 shows an example of a prediction error sequence for a chest wall file recorded while the subject was breathing and after the subject had exercised.

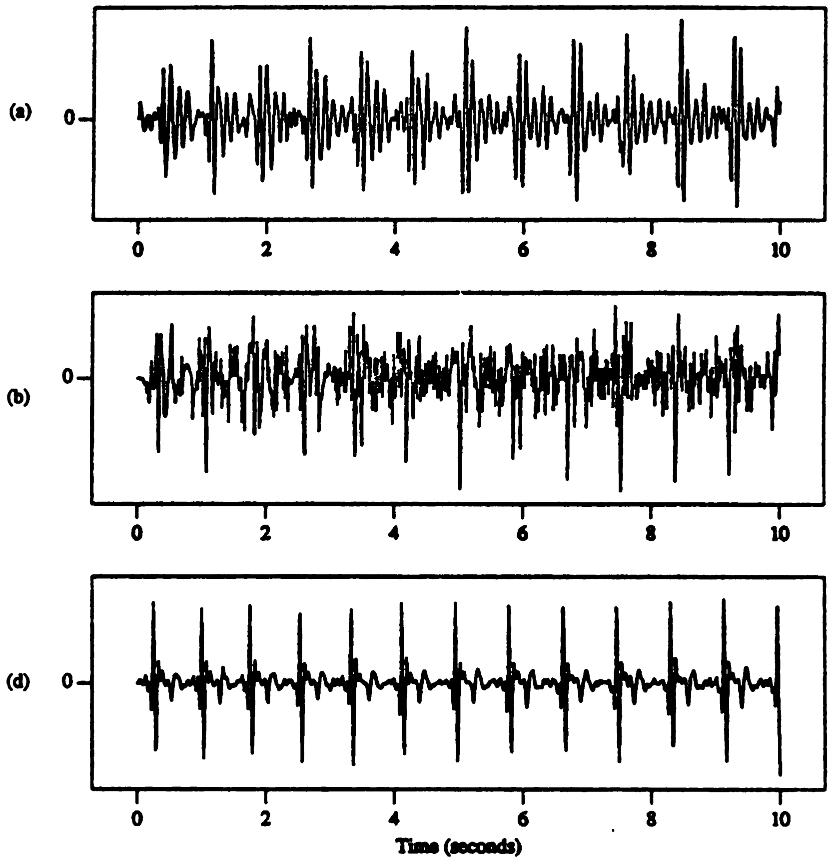


Figure 10. Recovered excitation process for a chest wall file recorded under ideal conditions. (a) chest wall microwave signal. (b) prediction error sequence. (c) hand potential heartbeat signal.

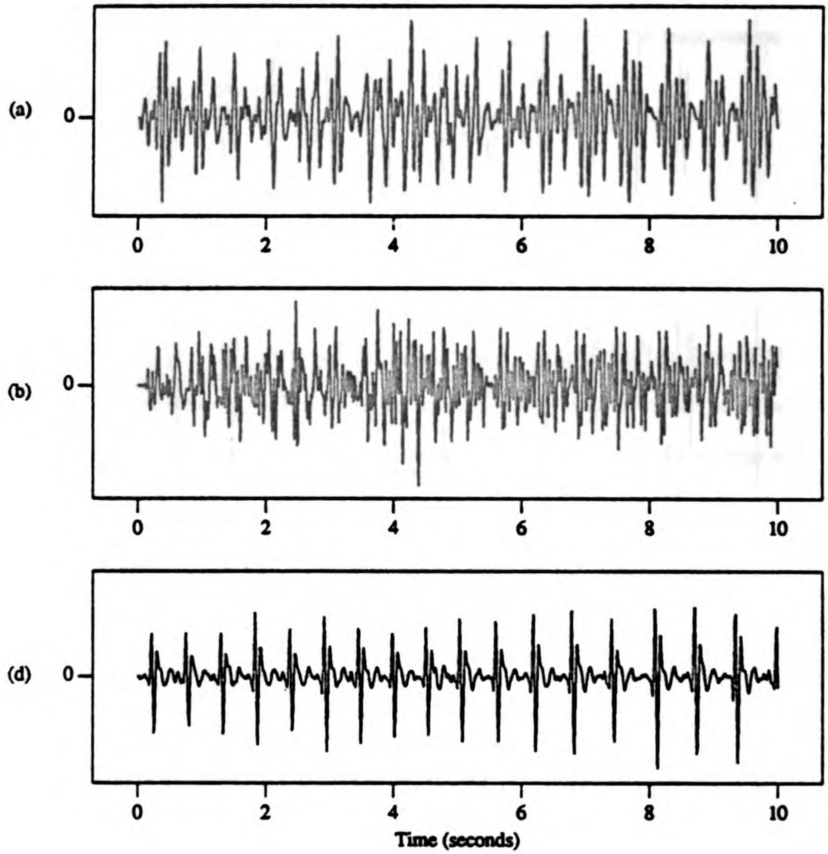


Figure 11. Recovered excitation process for a chest wall file recorded under more realistic conditions. (a) chest wall microwave signal. (b) prediction error sequence. (c) hand potential heartbeat signal.

The occurrence of large prediction errors that can be associated with heartbeats from the hand potential reference file is not consistent for the chest wall files. The behavior observed that was consistent from one chest wall file to the other was the behavior of the likelihood variable. For most of the chest wall files, there is a hump in the likelihood variable sequence for most of the heartbeats in the hand potential reference signal.

HEARTBEAT DETECTION WITH THE LIKELIHOOD VARIABLE

This section presents the results of an investigation into the feasibility of developing a heartbeat detector using only the likelihood variable. Heartbeats were detected by applying an arbitrary threshold of 0.5 to the likelihood variable sequences of all the chest wall files. If the value of the likelihood variable remained at or above 0.5 for 4 consecutive points, a likelihood variable cluster was formed. Note that the likelihood variable sequences were produced by a lattice filter with $\lambda = 0.90$. In order to verify that a file's likelihood variable cluster sequence represents the file's heartbeat signal, each likelihood variable cluster was classifyed as a heartbeat cluster or a non-heartbeat cluster depending on the location of the cluster in relation to the heartbeats of the hand potential reference signal of the file. A cluster was classifyed as a heartbeat cluster if the cluster occurred during the period between the reference heartbeat to the halfway point to the next reference heartbeat. If a cluster occurred during the period between the halfway point and the next heartbeat, the cluster was classifyed as a non-heartbeat cluster.

The number of heartbeat clusters, the number of non-heartbeat clusters, and the number of heartbeats in the reference signal were tabulated for each chest wall and leg file from the data base. Appendix D contains the tabulation of these results. The percentage of reference heartbeats associated with a likelihood variable cluster was calculated for each file and was recorded as the percentage of hits. The percentage of likelihood variable clusters not associated with reference heartbeats was calculated for èach file and was recorded as the percent of false alarms. Figure 12 shows an example of thresholding the likelihood variable sequence for a chest wall file. Figure 13 shows the result of thresholding the likelihood variable sequence for a leg file.

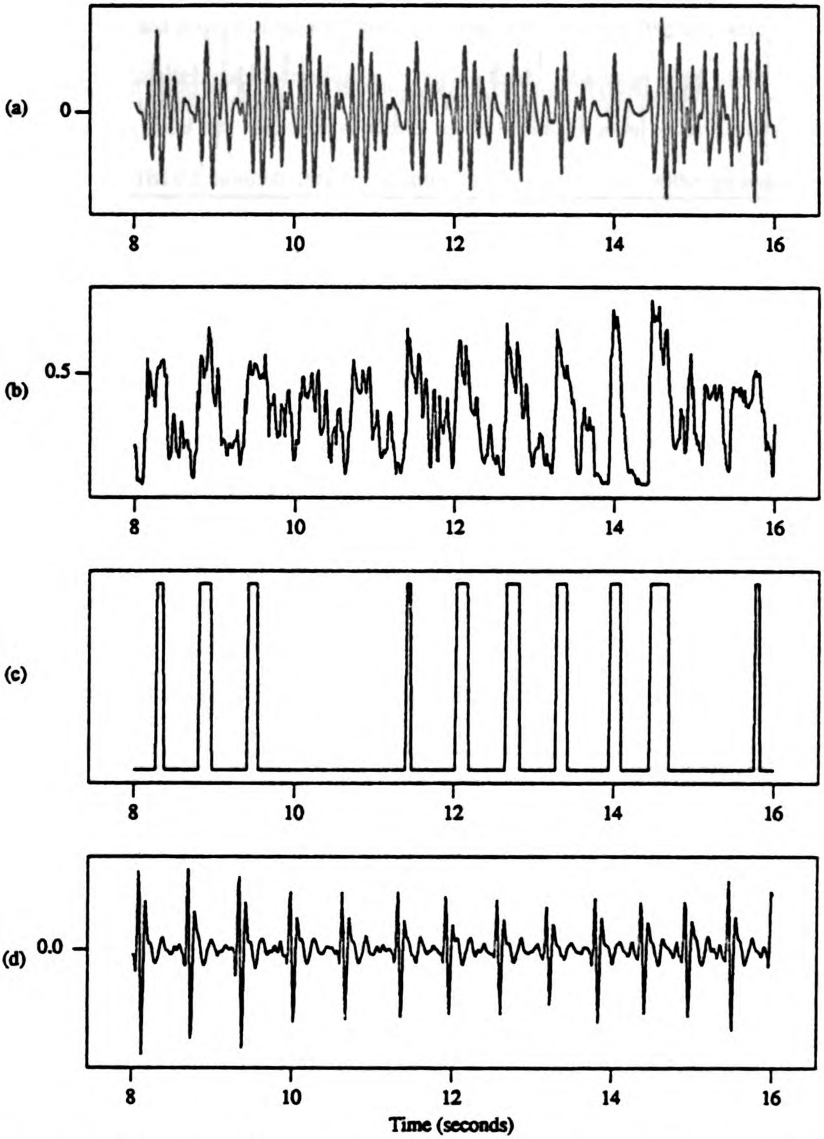


Figure 12. A chest wall file example of thresholding the likelihood variable. (a) chest wall microwave signal. (b) original likelihood variable sequence. (c) likelihood variable cluster sequence. (d) hand potential heartbeat signal.

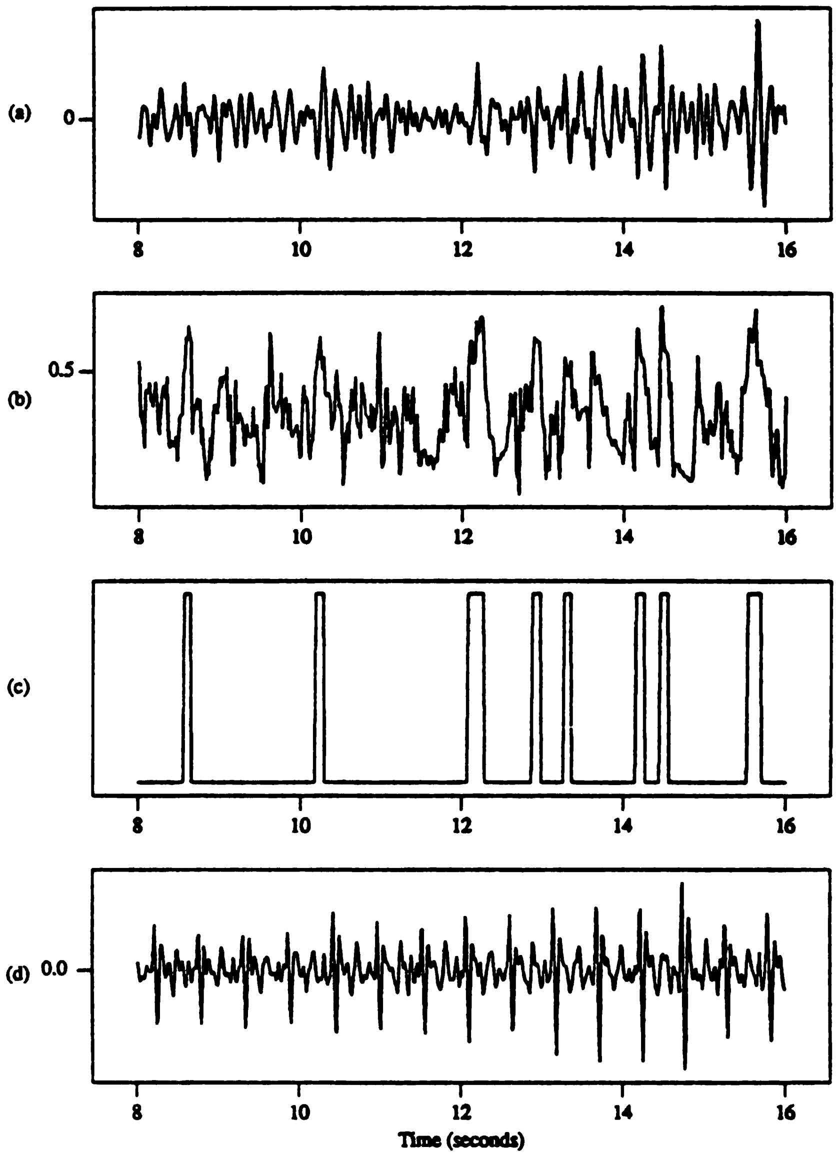


Figure 13. A leg file example of thresholding the likelihood variable. (a) leg microwave signal. (b) original likelihood variable sequence. (c) likelihood variable cluster sequence. (d) hand potential heartbeat signal.

For three of the classifications of the chest wall files, the percentage of heartbeats detected is about 80% and the rate of false alarms is less than 20%. Thresholding the likelihood variable at 0.5 is far from being an optimal detector. Figure 12 shows sections of the likelihood variable sequence that were not identified as heartbeats yet by sight seem to be obvious heartbeats occurrences. The 0.5 threshold may be too stringent of a requirement. Although some heartbeats were not detected, the periodicity of the detected heartbeats could be used in the estimation of heart rate through a technique such as autocorrelation.

The percentage of detected heartbeats for the leg data was low, 50%. The rate of false alarms for the leg data, 30%, was higher then the false alarm rate for the chest wall data. The low heartbeat detection rate and the higher false alarm rate for the leg data indicates that likelihood variable cluster sequence resulting from thresholding a leg likelihood variable sequence at 0.5 does not correlate with the hand potential reference heartbeat signal. Each leg file had 18 to 20 likelihood variable clusters while the number of heartbeats in the hand potential signals varied from 35 to 20. The constant number of likelihood variable clusters for the leg files and the varying numbers of heartbeats in the reference files helps support the conclusion that the likelihood variable clusters of the leg files do not correlate to the heartbeats in the hand potential reference signal.

CONCLUSIONS

The primary objective of this research was to verify that the Byrne and Siegel (1985) model and heartbeat detection method are appropriate for microwave heartbeats signals recorded from the modified monitor. The Byrne and Siegel model seems to hold for only a few chest wall files from the data base. The files were recorded under ideal conditions for heartbeat detection. The subjects were still and holding their breath. Distinctive large prediction errors are coincident with the occurrence of heartbeats in the hand potential reference signals for these files. For files recorded with more movement of the chest wall, the Byrne and Siegel model does not seem to hold as well. In these files, the prediction errors that are near heartbeat locations are not distinguishable from prediction errors between heartbeat occurrences. The Byrne and Siegel model may not sufficiently characterize the microwave heartbeat signal when there is chest wall movement due to sources other than the heart beating.

When linear prediction is used to deconvolve a process, it is assumed that the process is the result of exciting an all-pole filter that has all of it poles and zeros inside the unit circle. This implies that the systems linear prediction can inverse are minimum-phase. If the system the heartbeat signal passes through is not minimum-phase, adaptive linear prediction will not exactly deconvolve the microwave heartbeat signal. The prediction error sequence would probably not resemble the original excitation process. If the microwave heartbeat signal is the output of a non-minimum-phase system, the prediction error sequences resulting from processing the microwave heartbeat signal files recorded when the subjects were breathing may be expected.

Linear prediction may not exactly deconvolve the microwave heartbeat signal even if the minimum-phase all-pole filter model held for the microwave heartbeat signal. If the all-pole filter is excited by a white process or a single impulse, linear prediction can exactly deconvolve the output of the all-pole filter. A white process or a single impulse are uncorrelated processes. Both processes have flat spectra. An impulse train is correlated. The linear prediction may be biased for a process that results from exciting an all-pole filter with a correlated input. The correlation information of the excitation process may be absorbed in the linear prediction. The prediction error sequence will be something other than the process that excited the all-pole filter. The prediction error will be more white that the original excitation process. If the microwave heartbeat signal could be modeled as the output of an all-pole filter excited by an impulse train, the impulse train may not be recoverable from the prediction errors because of imperfect deconvolution.

The all-pole coefficients were obtain in the hope of gaining new information that might help in the development of a heart rate estimation technique. It was found that the configuration of the all-pole filter was uniform for the data base files. The data base files are the result of reflecting microwave signals off very different surfaces. One thing that all the data base files have in common is the monitor. The all-pole filter in the Byrne and Siegel (1985) model may be modeling the monitor.

The likelihood variable was the most consistent source of information about the location of heartbeats in the microwave signals of this data base. The fact that the isolation of prediction errors associated with heartbeats in the Byrne and Siegel (1985) heartbeat detection technique relies on the likelihood variable sequence supports the conclusion that the likelihood variable is a good source of information about the location of heartbeats in the microwave signals. The investigation into the use of the likelihood variable alone in the detection of heartbeats showed that it may be feasible to estimate heart rate from the likelihood variable sequence for the data base chest wall files. The likelihood variable of the lattice filter is probably not the optimal way of detecting changes in the statistics of a stochastic process. Other methods of detecting changes in the statistics of stochastic processes should be considered before a method using the lattice filter likelihood variable to detect heartbeats in the microwave heartbeat signals is developed.

In conclusion, the Byrne and Siegel (1985) model and heartbeat detection technique should not be accepted or rejected for the signals recorded from the modified monitor before the validity of the assumptions of the model and detection technique are investigated. If the Byrne and Siegel model is valid for signals recorded from the modified monitor, it appears that the configuration of the all-pole filter is uniform for the files in the data base. The consistent behavior of the likelihood variable for the files of the data base suggests that heartbeats in the microwave heartbeat signal can be identifiable by the detection of changes in the statistics of the microwave heartbeat signals.

RECOMMENDATIONS

1. The Byrne and Siegel (1985) study and this research considered only one pitch pulse detector. Because of the similarity between the problems of finding pitch pulses in speech processes and detecting heartbeats in the microwave heartbeat signals, other pitch pulse detection techniques should be investigated. The study of other pitch pulse detection techniques might reveal more information about the limitations of using linear prediction and ways to overcome those limitations. Methods other than linear prediction that can be used to detect heartbeats from the microwave signals may be found.

2. The consequences of using linear prediction to inverse the operation of a non-minimum-phase system should be investigated. This problem has been researched in the area of speech analysis.

3. The consequences of using linear prediction to deconvolve a process that results from exciting an all-pole filter with a correlated process should be investigated. This problem has been research in the area of pitch pulse detection in speech processes.

4. If the development of a method of identifying heartbeats in the microwave heartbeat signal by detecting changes in the statistics of the microwave signal is to be pursued, methods of detecting changes in the statistics of stochastic process should be studied.

5. It is possible that the all-pole filter of the Byrne and Siegel (1985) model is modeling the monitor. It may be useful to see how changing the configuration of the monitor effects the configuration of the all-pole filter. The configuration of the monitor may be affecting how well linear prediction can perform in the detection of heartbeats in the microwave signals.

APPENDICES

APPENDIX A

SAMPLES OF FILES FROM THE DATA BASE

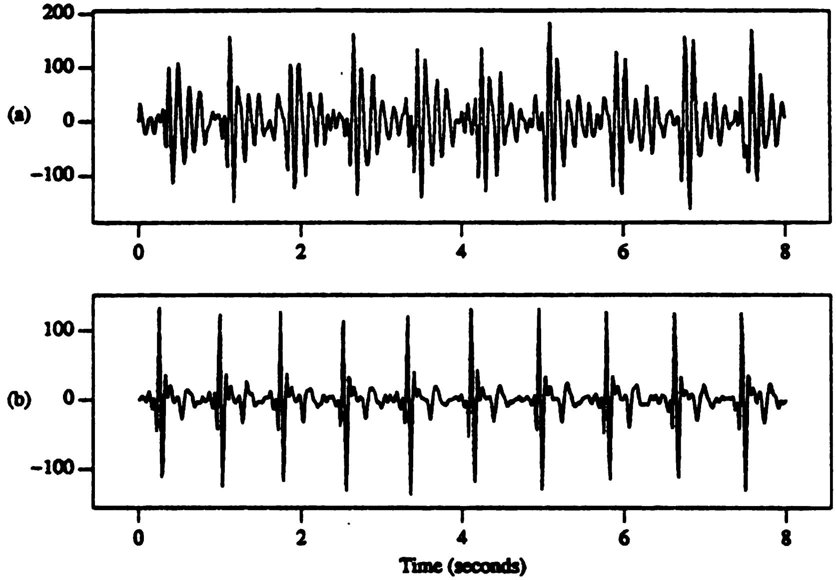


Figure A1. Chest wall file with human subject at rest and holding breath. (a) microwave signal. (b) hand potential reference signal

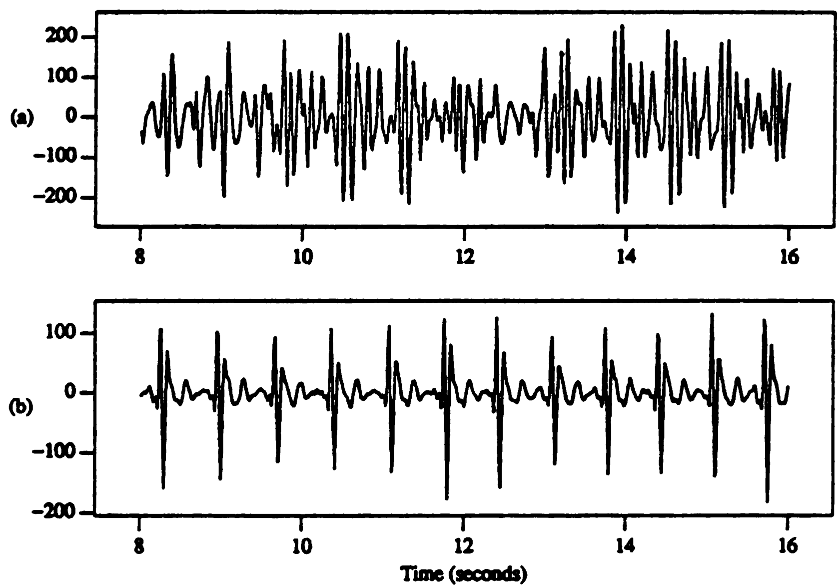


Figure A2. Chest wall file with human subject at rest and breathing. (a) microwave signal. (b) hand potential signal.

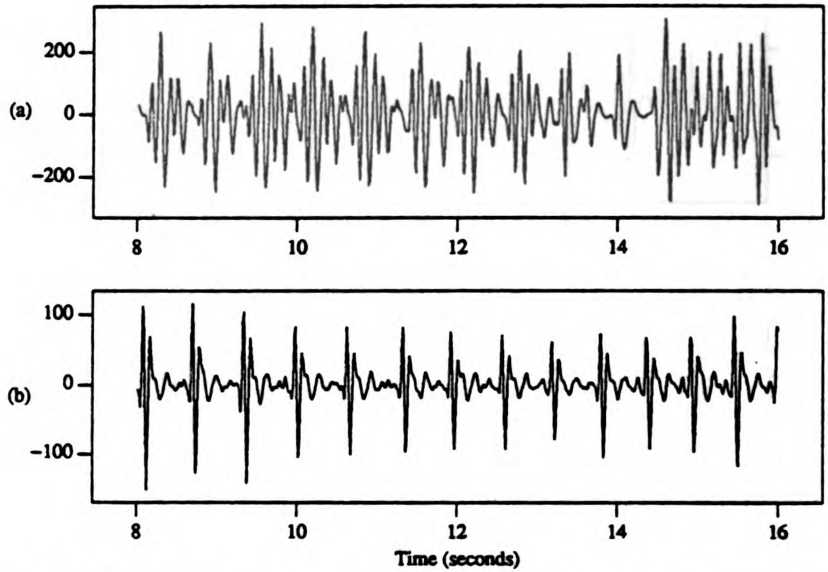


Figure A3. Chest wall file with human subject exercised and holding breath. (a) microwave signal. (b) hand potential reference signal

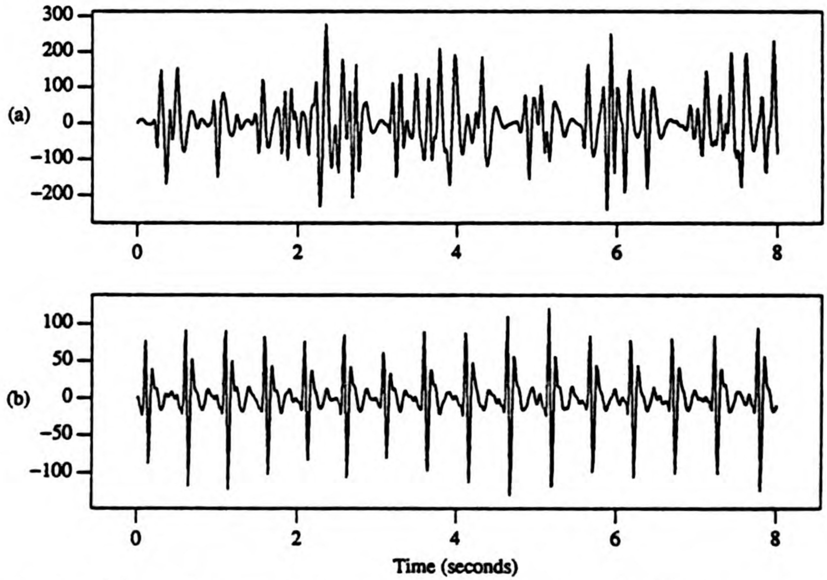


Figure A4. Chest wall file with human subject exercised and breathing. (a) microwave signal. (b) hand potential signal.

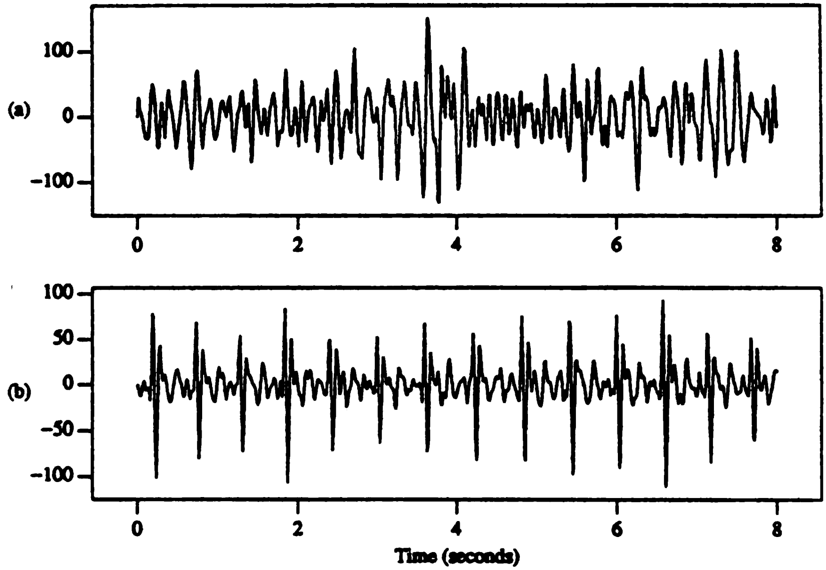


Figure A5. Leg file of a human subject. (a) microwave signal. (b) hand potential reference signal

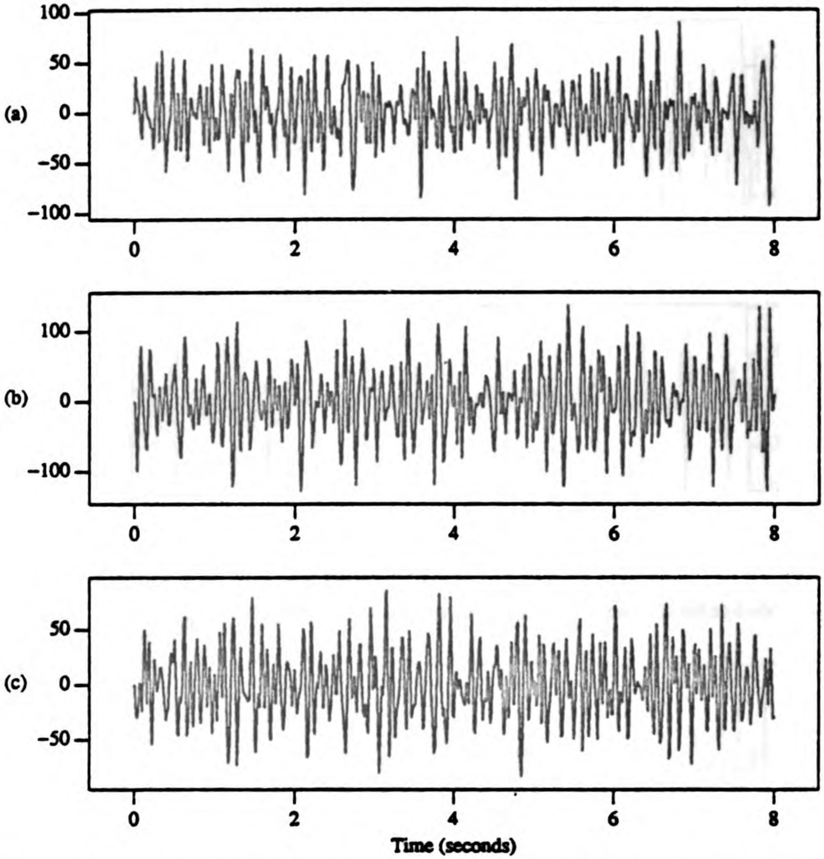


Figure A6. Inanimate object files. (a) microwave signal for wool surface. (b) microwave signal for metal surface. (c) microwave signal for open room.

APPENDIX B

PREDICTION ERROR VARIANCES USED TO DETERMINE ALL-POLE FILTER ORDER

Table B1. Prediction Error Variances Used to Determine All-Pole Filter Order

File Type	Prediction Error Variance					
	Order					
	1	2	3	4	5	6
Human Subjects at rest and holding breath.						
Subject 1	1557	342	274	142	137	125
Subject 2	1129	454	349	167	152	144
Subject 3	4855	1217	886	474	421	376
Subject 4	2183	551	416	201	189	180
Human Subjects at rest and breathing.						
Subject 2	587	219	162	63	59	56
Subject 3	4195	1115	784	351	305	247
Subject 4	980	295	225	92	88	86
Human Subjects exercised and holding breath.						
Subject 1	3564	1098	781	325	272	248
Subject 2	2531	859	549	302	274	235
Subject 3	5833	1285	936	476	409	336
Subject 4	1965	563	388	152	136	119
Human Subjects exercised and breathing.						
Subject 1	2858	1006	687	359	319	252
Subject 2	1925	614	442	208	190	166
Subject 3	3287	1029	718	342	308	253
Subject 4	2237	725	501	203	170	135
Human Subjects' legs.						
Subject 1	2026	558	407	174	153	130
Subject 2	2028	624	408	194	176	153
Subject 3	985	289	208	110	105	101
Subject 4	1180	393	280	119	106	93
Inanimate Objects.						
Wool Surface	659	316	276	201	198	188
Metal Surface	1415	566	484	292	275	228
Open Room	775	333	289	184	181	161

APPENDIX C

ALL-POLE FILTER COEFFICIENTS

Table C1. All-Pole Filter Coefficients

File Type	All-Pole Filter Coefficients			
	A_1	A_2	A_3	A_4
Human Subjects at rest and holding breath.				
Subject 1	-1.864	2.397	-1.534	.7052
Subject 2	-1.898	2.298	-1.607	.7369
Subject 3	-2.055	2.562	-1.696	.7027
Subject 4	-1.984	2.512	-1.670	.7320
Human Subjects at rest and breathing.				
Subject 2	-1.631	2.140	-1.467	.7745
Subject 3	-1.991	2.526	-1.716	.7363
Subject 4	-1.931	2.431	-1.651	.7550
Human Subjects exercised and holding breath.				
Subject 1	-2.117	2.548	-1.739	.6786
Subject 2	-1.980	2.426	-1.647	.6597
Subject 3	-2.081	2.576	-1.684	.6735
Subject 4	-2.047	2.630	-1.806	.7732
Human Subjects exercised and breathing.				
Subject 1	-1.775	2.360	-1.594	.7788
Subject 2	-2.116	2.589	-1.780	.7189
Subject 3	-2.111	2.604	-1.781	.7223
Subject 4	-1.899	2.438	-1.687	.7792
Human Subjects' legs.				
Subject 1	-2.025	2.551	-1.730	.7449
Subject 2	-2.049	2.561	-1.739	.7129
Subject 3	-2.143	2.575	-1.734	.6786
Subject 4	-1.991	2.482	-1.730	.7555
Human Subject Means	-1.984	2.485	-1.684	.7273
Inanimate Objects.				
Wool Surface	-1.301	1.497	-0.831	.5089
Metal Surface	-1.480	1.861	-1.220	.6830
Open Room	-1.286	1.683	-0.989	.6064
Inanimate Objects Means	-1.356	1.680	-1.013	.5994

APPENDIX D

THE RESULTS OF THRESHOLDING THE LIKELIHOOD VARIABLE SEQUENCE AS A HEARTBEAT DETECTION METHOD

Table D1. The Results of Thresholding the Likelihood Variable Sequence as a Method of Detecting Heartbeats

File	Actual Heartbeat Count	Number of Clusters	Number of Hits	% Hits	Number of False Alarms	% False Alarms
Human Subjects at rest and holding breath.						
Subject 1	20	19	17	85	2	10
Subject 2	17	17	19	100	0	0
Subject 3	23	24	19	83	5	21
Subject 4	24	23	19	79	4	18
Means				85		12
Human Subjects at rest and breathing.						
Subject 2	14	20	14	100	6	30
Subject 3	23	20	18	78	2	10
Subject 4	25	21	17	68	4	19
Means				82		19
Human Subjects exercised and holding breath.						
Subject 1	37	28	25	68	3	10
Subject 2	14	23	13	92	10	43
Subject 3	27	23	22	81	1	4
Subject 4	24	23	21	87	2	9
Means				81		17
Human Subjects exercised and breathing.						
Subject 1	30	22	15	50	7	31
Subject 2	26	21	19	73	2	9
Subject 3	31	25	22	70	3	12
Subject 4	32	23	21	66	2	9
Means				64		15
Human Subjects' legs.						
Subject 1	23	20	14	60	6	30
Subject 2	21	18	15	71	3	16
Subject 3	29	18	12	41	6	33
Subject 4	35	18	11	31	7	38
Means				50		30

APPENDIX E

THE UNNORMALIZED PRE-WINDOWED LEAST SQUARES LATTICE FILTER PARAMETER UPDATE ALGORITHM

This appendix gives the parameter update algorithm used for the Unnormalized Pre-Windowed Least Squares Lattice Filter. The algorithm came from Friedlander (1982a, p. 844). The algorithm found in Friedlander is for the multi-channel case. This means that all of the variables in the algorithm presented in Friedlander are either vectors or matrices. The scalar case was used in this thesis research. This means that all of the variables in the lattice filter update algorithm were scalars. The scalar version of the algorithm is given in this appendix.

Input parameters:

M = maximum order of lattice

y_T = data sequence at time T

λ = exponential weighting factor

Variables:

$R^{\varepsilon}_{p,T}$ = sample covariance of forward errors

$R^{r}_{p,T-1}$ = sample covariance of backward errors

$\Delta_{p,T}$ = sample partial correlation coefficient

$\gamma^{c}_{p,T} = 1 - \gamma_{p,T}$ = 1 - likelihood variable

$\varepsilon_{p,T}$ = forward prediction errors

$r_{p,T-1}$ = backward prediction errors

$K^{\varepsilon}_{p,T}$ = forward reflection coefficients

$K^{r}_{p,T}$ = backward reflection coefficients

The following computations will be performed once for every time step (T=0, . . . , TMAX).

Initialize:

$\varepsilon_{0,T} = r_{0,T} = y_T$

$R^{\varepsilon}_{0,T} = R^{r}_{0,T} = \lambda R^{\varepsilon}_{0,T-1} + y_T y_T$

$\gamma^{c}_{-1,T} = 1$

Do for p = 0 to min(M,T) - 1

$\Delta_{p+1,T} = \lambda \Delta_{p+1,T-1} + \varepsilon_{p,T} r_{p,T-1} / \gamma^{c}_{p-1,T-1}$ *

$\gamma^{c}_{p,T} = \gamma^{c}_{p-1,T} - r_{p,T} r_{p,T} / R^{r}_{p,T}$ *

$K^{r}_{p+1,T} = \Delta_{p+1,T} / R^{r}_{p,T-1}$ *

$\varepsilon_{p+1,T} = \varepsilon_{p,T} - K^{r}_{p+1,T} r_{p,T-1}$

$R^{\varepsilon}_{p+1,T} = R^{\varepsilon}_{p,T} - K^{r}_{p+1,T} \Delta_{p+1,T}$

$K^{\varepsilon}_{p+1,T} = \Delta_{p+1,T} / R^{\varepsilon}_{p,T}$ *

$r_{p+1,T} = r_{p,T-1} - K^{\varepsilon}_{p+1,T} \varepsilon_{p,T}$

$$R^{r}_{p+1,T} = R^{r}_{p,T-1} - \Delta_{p+1,T} K^{\varepsilon}_{p+1,T}$$

Note: Only the variables Δ, R^{ε}, R^{r}, γ^{c}, r need to be stored from one time step to the other. They are all set initially to zero. The quantities R^{r}, γ^{c}, r need to be stored twice to avoid "overwriting".

When the divisor $x = \gamma^{c}, R^{r}, R^{\varepsilon}$ is very small, set $1/x = 0$ in the equations marked with *.

APPENDIX F

COMPUTING THE ALL-POLE FILTER COEFFICIENTS FROM THE UNNORMALIZED LATTICE PARAMETERS

This appendix gives the algorithm that was used to compute the all-pole filter coefficients from the Unnormalized Pre-Windowed Least Squares Lattice Filter parameters. The algorithm came from Friedlander (1982a, p. 845). The transfer function of the all-pole filter has been rewritten in [B1] so that the notation corresponds to the algorithm presented in this appendix.

$$H_{all-pole\ filter}(z) = \left[\frac{1}{1 + \sum_{i=1}^{p} A_{p,i} z^{-i}} \right], \qquad \text{[B1]}$$

where p is the order of the all-pole filter. The following algorithm was used to update the estimation of the all-pole filter coefficients from the lattice parameters for each time step. Recall that for the lattice filter of order M all lower order lattice filters are available in its structure. This means that the parameters of lattice filters of orders lower than M are available from the parameter update algorithm of a lattice filter of order M. The following algorithm computes the coefficients of the all-pole filter corresponding with the lattice filter of order M and the coefficients of the all-pole filters of all lower orders. The all-pole coefficients are designated by $A_{p,i}$ where p is the order of the all-pole filter.

Note that the algorithm in Friedlander (1982a, p. 845) is for the multi-channel case. This means that the parameters of the algorithm are either vectors or matrices. The scalar case was used in this research. Therefore, the following algorithm is for the scalar case. This means that the parameters of the following algorithm are scalars.

Inputs:

M = maximum order of the lattice

r_p = backward error for the current time step

γ_p^c = likelihood variable for current time step

K_p^ε = forward reflection coefficient for the current time step

K_p^r = backward reflection coefficient for the current time step

R_p^r = sample covariance for backward errors for the current time step

Variables:

$A_{p,i}$ = all-pole filter coefficients

$B_{p,i}$, $B^*_{p,i}$, $C_{p,i}$

These computations will be performed each time it is desired to update the all-pole filter coefficients.

Initialize:

$B^*_{p,-1} = 0$ for $p = 0, \ldots, M-1$

$C_{0,0} = 0$

For $i = 0, \ldots, M$

$A_{0,i} = B_{0,i} = 1 \quad \text{for } i = 0$

$A_{0,i} = B_{0,i} = 0 \quad \text{for } i > 0$

Do for $p = 0, \ldots, M-1$

$$B^{*}_{p,i} = B_{p,i} - r_p C_{p,i} / \gamma^{c}_{p-1}$$

$$C_{p+1,i} = C_{p,i} - r_p B_{p,i} / R^{r}_{p}$$

$$A_{p+1,i} = A_{p,i} - K^{r}_{p+1} B^{*}_{p,i-1}$$

$$B_{p+1,i} = B_{p,i-1} - K^{\ell}_{p+1} A_{p,i}$$.ps 11

APPENDIX G

A FORTRAN IMPLEMENTATION OF THE UNNORMALIZED PRE-WINDOWED LEAST SQUARES LATTICE FILTER

The Unnormalized Pre-Windowed Least Squares Lattice Filter was implemented in two parts, a data structure holding the lattice parameters and the parameter update algorithm. Microsoft Fortran was used for the implementation. The lattice data structure is contained in a labeled common block. The lattice parameter update algorithm is contained in a subroutine. The parameter update algorithm is to be called for each new time step. The Fortran code for the lattice data structure and parameter update algorithm is given below.

```
****************************************************************************
LATTICE.DST

THIS FILE DEFINES THE UNNORMALIZED PRE-WINDOWED LEAST SQUARES LAT-
TICE ALGORITHM DATA STRUCTURE. THE ALGORITHM WAS TAKEN FROM:
FRIEDLANDER, B., LATTICE FILTERS FOR ADAPTIVE PROCESSING, PROCEEDINGS
    OF THE IEEE, VOL. 70, NO.8, AUGUST 1982, pp. 842-844.

DEFINITIONS:
COMMON/LATTICE/ - LABELED COMMON THAT CONTAINS THE LATTICE DATA
    STRUCTURE
RE - ARRAY CONTAINING SAMPLE COVARIANCES OF FORWARD ERRORS. EACH
    ELEMENT OF THE ARRAY CORRESPONDS TO THE COVARIANCE OF THE
```

FORWARD ERROR FOR A PARTICULAR ORDER. NOTE THAT THERE IS AN OFFSET BETWEEN THE ARRAY INDEX AND ORDER. ARRAY INDEX 1 CORRESPONDS TO ORDER 0.

RR - ARRAY CONTAINING SAMPLE COVARIANCES OF BACKWARD ERRORS. EACH ELEMENT OF THE ARRAY CORRESPONDS TO THE COVARIANCE OF THE FORWARD ERROR FOR A PARTICULAR ORDER. NOTE THAT THERE IS AN OFFSET BETWEEN THE ARRAY INDEX AND ORDER. ARRAY INDEX 1 CORRESPONDS TO ORDER 0.

RRCOPY - ARRAY CONTAINING SAMPLE COVARIANCES OF BACKWARD ERRORS FOR THE PREVIOUS TIME STEP. EACH ELEMENT OF THE ARRAY CORRESPONDS TO THE COVARIANCE OF THE FORWARD ERROR FOR A PARTICULAR ORDER. NOTE THAT THERE IS AN OFFSET BETWEEN THE ARRAY INDEX AND ORDER. ARRAY INDEX 1 CORRESPONDS TO ORDER 0.

PARCORR -ARRAY CONTAINING SAMPLE PARTIAL CORRELATION COEFFICIENTS. EACH ELEMENT OF THE ARRAY CORRESPONDS TO THE COVARIANCE OF THE FORWARD ERROR FOR A PARTICULAR ORDER. NOTE THAT THERE IS AN OFFSET BETWEEN THE ARRAY INDEX AND ORDER. ARRAY INDEX 1 CORRESPONDS TO ORDER 0.

LHOOD - ARRAY CONTAINING THE LIKELIHOOD VARIABLE. EACH ELEMENT OF THE ARRAY CORRESPONDS TO THE COVARIANCE OF THE FORWARD ERROR FOR A PARTICULAR ORDER. NOTE THAT THERE IS AN OFFSET BETWEEN THE ARRAY INDEX AND ORDER. ARRAY INDEX 1 CORRESPONDS TO ORDER -1.

LHOODCOPY - ARRAY CONTAINING THE LIKELIHOOD VARIABLE FOR THE PREVIOUS TIME STEP. EACH ELEMENT OF THE ARRAY CORRESPONDS TO THE COVARIANCE OF THE FORWARD ERROR FOR A PARTICULAR ORDER. NOTE THAT THERE IS AN OFFSET BETWEEN THE ARRAY INDEX AND ORDER. ARRAY INDEX 1 CORRESPONDS TO ORDER -1.

EERR - ARRAY CONTAINING FORWARD PREDICTION ERRORS. EACH ELEMENT OF THE ARRAY CORRESPONDS TO THE COVARIANCE OF THE FORWARD ERROR FOR A PARTICULAR ORDER. NOTE THAT THERE IS AN OFFSET BETWEEN THE ARRAY INDEX AND ORDER. ARRAY INDEX 1 CORRESPONDS TO ORDER 0.

RERR - ARRAY CONTAINING BACKWARD PREDICTION ERRORS. EACH ELEMENT OF THE ARRAY CORRESPONDS TO THE COVARIANCE OF THE FORWARD ERROR FOR A PARTICULAR ORDER. NOTE THAT THERE IS AN OFFSET BETWEEN THE ARRAY INDEX AND ORDER. ARRAY INDEX 1 CORRESPONDS TO ORDER 0.

RERRCOPY - ARRAY CONTAINING BACKWARD PREDICTION ERRORS FOR THE PREVIOUS TIME STEP. EACH ELEMENT OF THE ARRAY CORRESPONDS TO THE COVARIANCE OF THE FORWARD ERROR FOR A PARTICULAR ORDER. NOTE THAT THERE IS AN OFFSET BETWEEN THE ARRAY INDEX AND ORDER. ARRAY INDEX 1 CORRESPONDS TO ORDER 0.

KE - ARRAY CONTAINING FORWARD REFLECTION COEFFICIENTS. EACH ELEMENT OF THE ARRAY CORRESPONDS TO THE COVARIANCE OF THE FORWARD ERROR FOR A PARTICULAR ORDER. NOTE THAT THERE IS AN OFFSET BETWEEN THE ARRAY INDEX AND ORDER. ARRAY INDEX 1 CORRESPONDS TO ORDER 0.

KR - ARRAY CONTAINING BACKWARD REFLECTION COEFFICIENTS. EACH ELEMENT OF THE ARRAY CORRESPONDS TO THE COVARIANCE OF THE

FORWARD ERROR FOR A PARTICULAR ORDER. NOTE THAT THERE IS AN OFFSET BETWEEN THE ARRAY INDEX AND ORDER. ARRAY INDEX 1 CORRESPONDS TO ORDER 0.

MAXORDER - MAXIMUM ORDER OF THE LATTICE FILTER.

(NOTE: INDEX 1 CORRESPONDS TO THE ZEROTH ORDER, EXCEPT FOR THE LIKELIHOOD VARIABLE WHERE INDEX 1 CORRESPONDS TO ORDER -1. THIS INCONVENIENT INDEXING METHOD IS DUE TO LIMITATION OF THE FORTRAN COMPILER BEING USED.)

```
****************************************************************************

      REAL RE(10), RR(10), RRCOPY(10), PARCORR(10)
      REAL LHOOD(10), EERR(10), RERR(10), RERRCOPY(10)
      REAL KE(10), KR(10), LHOODCOPY(10)
      INTEGER MAXORDER

       COMMON/LATTICE/ RE, RR, RRCOPY, PARCORR, LHOOD, LHOODCOPY,
      EERR, RERR, RERRCOPY, KE, KR, MAXORDER

****************************************************************************

      SUBROUTINE UPDATELATTICE( DATA, ORDER, WEIGHT, TIME, LIMLHOOD,
      PARMLIM)

****************************************************************************
```

SUBROUTINE UPDATELATTICE

THIS SUBROUTINE UPDATES THE UNNORMALIZED LEAST SQUARES LATTICE DATA STRUCTURE FOR A TIME STEP. THE UPDATE ALGORITHM WAS TAKEN FROM:

FRIEDLANDER, B., LATTICE FILTERS FOR ADAPTIVE PROCESSING, PROCEEDINGS OF THE IEEE, VOL. 70, NO.8 AUGUST 1982, pp 842-844.

INPUT:

COMMON/LATTICE/ - LATTICE DATA STRUCTURE (SEE LATTICE.DST)

ORDER - MAXIMUM ORDER OF THE LATTICE FILTER.

WEIGHT - EXPONENTIAL WEIGHTING FACTOR FOR PAST DATA.

LIMLHOOD - IF THE ABSOLUTE VALUE OF LHOOD OR LHOODCOPY IS LESS THAN LIMLHOOD, LHOOD OR LHOODCOPY WILL BE CONSIDERED TO BE ZERO.

PARMLIM - IF ANY VARIABLES OF THE LATTICE FILTER EXCEPT FOR LHOOD AND LHOODCOPY HAS ABSOLUTE VALUE LESS THAN PARMLIM, THE VARIABLES WILL BE CONSIDERED TO BE ZERO.

DATA - A DATA POINT FROM A DATA SEQUENCE.

TIME - CURRENT TIME STEP

OUTPUT:

COMMON/LATTICE/ - LATTICE DATA STRUCTURE

```
***************************************************************************

$INCLUDE: 'LATTICE.DST'

        REAL DATA,WEIGHT,LIMLHOOD,PARMLIM
        INTEGER TIME,ORDER,P

        ** INITIALIZATION

        EERR(1)  = DATA
        RERR(1)  = DATA
        RE(1)    = WEIGHT*RE(1) + DATA*DATA
        RR(1)    = RE(1)
        LHOOD(1) = 1

        ** LATTICE STAGE UPDATES

        DO 100 P = 1,(MIN(ORDER,TIME))

          IF (LHOODCOPY(P) .LT. LIMLHOOD) THEN
            PARCORR(P+1) = WEIGHT*PARCORR(P+1)
          ELSE
            PARCORR(P+1) = WEIGHT*PARCORR(P+1) + EERR(P) * RERRCOPY(P) /
            LHOODCOPY(P)
          ENDIF

          IF (RR(P) .LT. PARMLIM) THEN
            LHOOD(P+1) = LHOOD(P)
          ELSE
            LHOOD(P+1) = LHOOD(P) - RERR(P)*RERR(P)/RR(P)
```

```
      ENDIF

      IF (RRCOPY(P) .LT. PARMLIM) THEN
         KR(P+1) = PARCORR(P+1)* 0.0
      ELSE
         KR(P+1) = PARCORR(P+1)/RRCOPY(P)
      ENDIF

      EERR(P+1) = EERR(P) - KR(P+1)*RERRCOPY(P)
      RE(P+1) = RE(P) - KR(P+1)*PARCORR(P+1)

      IF (RE(P)  .LT. PARMLIM) THEN
         KE(P+1) = PARCORR(P+1)* 0.0
      ELSE
         KE(P+1) = PARCORR(P+1)/RE(P)
      ENDIF

      RERR(P+1) = RERRCOPY(P) - KE(P+1)*EERR(P)
      RR(P+1) = RRCOPY(P) - PARCORR(P+1)*KE(P+1)

100   CONTINUE

      DO 200 P = 1,MAXORDER

         RRCOPY(P) = RR(P)
         RERRCOPY(P) = RERR(P)
         LHOODCOPY(P) = LHOOD(P)

200   CONTINUE


      RETURN
      END
```

APPENDIX H

A FORTRAN IMPLEMENTATION OF THE ALL-POLE FILTER COEFFICIENT UPDATE ALGORITHM

The all-pole filter coefficient update algorithm was implemented in two parts, a data structure holding the all-pole filter coefficients and the coefficient update algorithm. Microsoft Fortran was used for the implementation. The coefficients are contained in a labeled common block. The coefficient update algorithm is contained in a subroutine. The Fortran code for the coefficient data structure and the coefficient update algorithm is given below.

```
*****************************************************************************

LATCOEF.DST

THIS FILE DEFINES THE ALL-POLE FILTER COEFFICIENT DATA STRUCTURE. THE
ALGORITHM USED TO UPDATE THE ALL-POLE FILTER COEFFICIENTS WAS TAKEN
FROM:
FRIEDLANDER, B., LATTICE FILTERS FOR ADAPTIVE PROCESSING, PROCEEDINGS
      OF THE IEEE, VOL. 70, NO. 8, AUGUST 1982, pp. 844-845.
NOTE THAT THE VARIABLES IN THIS DATA STRUCTURE SHOULD BE INITIALIZED
TO ZERO BEFORE THEY ARE USED.

DEFINITIONS:
```

A(p,i) - MATRIX CONTAINING THE ALL-POLE FILTER COEFFICIENTS. p CORRESPONDS TO THE ORDER OF THE FILTER. i CORRESPONDS TO THE SPECIFIC COEFFICIENT IN THE p ORDER ALL-POLE FILTER. p = 1 CORRESPONDS TO THE ZEROTH ORDER.

B(p,i) - MATRIX CONTAINING PARAMETERS USED IN THE ALL-POLE FILTER COEFFICIENT UPDATE ALGORITHM. p CORRESPONDS TO THE ORDER OF THE FILTER. i CORRESPONDS TO THE SPECIFIC COEFFICIENT IN THE p ORDER ALL-POLE FILTER. p = 1 CORRESPONDS TO THE ZEROTH ORDER.

BSTAR(p,i) - MATRIX CONTAINING PARAMETERS USED IN THE ALL-POLE FILTER COEFFICIENT UPDATE ALGORITHM. p CORRESPONDS TO THE ORDER OF THE FILTER. i CORRESPONDS TO THE SPECIFIC COEFFICIENT IN THE p ORDER ALL-POLE FILTER. p = 1 CORRESPONDS TO THE -1TH ORDER.

C(p,i) - MATRIX CONTAINING PARAMETERS USED IN THE ALL-POLE FILTER COEFFICIENT UPDATE ALGORITHM. p CORRESPONDS TO THE ORDER OF THE FILTER. i CORRESPONDS TO THE SPECIFIC COEFFICIENT IN THE p ORDER ALL-POLE FILTER. p = 1 CORRESPONDS TO THE ZEROTH ORDER.

****

```
      REAL A(10,10), B(10,10), BSTAR(10,10), C(10,10)

      COMMON/LATCOEF/ A, B, BSTAR, C
```

****

```
      SUBROUTINE COEFCALCULATION(ORDER,PARMLIM,LIMLHOOD)
```

****

THIS SUBROUTINE UPDATES THE ALL-POLE FILTER COEFFICIENTS WITH THE UNNORMALIZED PRE-WINDOWED LEAST SQUARES LATTICE FILTER PARAMETERS. THE COEFFICIENT UPDATE ALGORITHM WAS TAKEN FROM:

FRIEDLANDER, B., LATTICE FILTERS FOR ADAPTIVE PROCESSING, PROCEEDINGS OF THE IEEE, VOL. 70, NO. 8, AUGUST 1982, pp. 844-845.

INPUTS:

COMMON/LATTICE/ - LATTICE DATA STRUCTURE (SEE LATTICE.DST IN APPENDIX C).

COMMON/LATCOEF/ - ALL-POLE FILTER COEFFICIENT DATA STRUCTURE (SEE LATCOEF.DST).

ORDER - MAXIMUM ORDER OF THE LATTICE FILTER.

PARMLIM - IF ANY VARIABLES OF THE LATTICE FILTER EXCEPT FOR LHOOD AND LHOODCOPY HAS AN ABSOLUTE VALUE LESS THAT PARMLIM, THE VARIABLES WILL BE CONSIDERED TO BE ZERO.

LIMLHOOD - IF LHOOD OR LHOODCOPY FROM THE LATTICE DATA STRUCTURE HAS AN ABSOLUTE VALUE LESS THAN LIMLHOOD, LHOOD OR LHOODCOPY WILL BE CONSIDERED TO BE ZERO.

OUTPUTS:

COMMON/LATCOEF/ - ALL-POLE FILTER COEFFICIENT DATA STRUCTURE (SEE LATCOEF.DST).

```
****************************************************************************

$INCLUDE: 'LATTICE.DST'
$INCLUDE: 'LATCOEF.DST'

        REAL PARMLIM,LIMLHOOD
        INTEGER ORDER,I,P

        DO 1000 I = 1, ORDER+1

           IF (I .EQ. 1) THEN
              A(1,I) = 1.0
              B(1,I) = 1.0
           ELSE
              A(1,I) = 0.0
              B(1,I) = 0.
           ENDIF

           DO 100  P = 1,ORDER

              IF (LHOOD(P)  .LT. LIMLHOOD) THEN
                 BSTAR(P,I+1) = B(P,I)
              ELSE
                 BSTAR(P,I+1) = B(P,I) - RERR(P)*C(P,I)/LHOOD(P)
              ENDIF
```

```
          IF (ABS(RR(P)) .LT. PARMLIM) THEN
             C(P+1,J) = C(P,J)
          ELSE
             C(P+1,J) = C(P,J) - RERR(P)*B(P,J)/RR(P)
          ENDIF

          A(P+1,J) = A(P,J) - KR(P+1)*BSTAR(P,J)
          B(P+1,J) = BSTAR(P,J) - KE(P+1) * A(P,J)

100       CONTINUE

1000  CONTINUE
      RETURN
      END
```

APPENDIX I

THE NORMALIZED PRE-WINDOWED LEAST SQUARES LATTICE FILTER

This appendix gives the parameter update algorithm used for the Normalized Pre-Windowed Least Squares Lattice Filter. The algorithm came from Friedlander (1982a, p. 846). In the normalized version of the lattice filter, the lattice parameters maintain an absolute value of less than unity. The algorithm found in Friedlander is for the multi-channel case. This means that all of the variables in the algorithm presented in Friedlander are either vectors or matrices. The scalar case was used in this thesis research. This means that all of the variables in the lattice filter update algorithm were scalars. The scalar version of the algorithm is given in this appendix. Please note that when Friedlander uses a T in a superscript on parameters in the normalized lattice filter parameter update algorithm the T means transpose and not time.

Input parameters:

M = maximum order of lattice

y_T = data sequence at time T

λ = exponential weighting factor

Variables:

S_T = estimated covariance of y_T

$\bar{\varepsilon}_{p,T}$ = normalized forward prediction errors

$\bar{r}_{p,T-1}$ = normalized backward prediction errors

$K_{p,T}$ = reflection coefficients

Initialization:

K, r, S are set to zero

The following computations will be performed once for every time step (T=0, . . . , TMAX).

$$S_T = \lambda S_{T-1} + y_T y_T$$

$$\bar{\varepsilon}_{0,T} = \bar{r}_{0,T} = S_T^{-1/2} y_T$$

For $p = 0, \ldots, \min(M,T) - 1$

$$K_{p+1,T} = F^{-1}(K_{p+1,T-1}, \bar{r}_{p,T-1}, \bar{\varepsilon}_{p,T})$$

$$\bar{\varepsilon}_{p+1,T} = F(\bar{\varepsilon}_{p,T}, \bar{r}_{p,T-1}, K_{p+1,T}) \quad *$$

$$\bar{r}_{p+1,T} = F(\bar{r}_{p,T-1}, \bar{\varepsilon}_{p,T}, K_{p+1,T}) \quad *$$

$$F(a,b,c) = [1 - cc]^{-1/2}[a - cb][1 - bb]^{-1/2}$$

$$F^{-1}(a,b,c) = [1 - cc]^{1/2} a [1 - bb]^{1/2} + cb$$

The function F(a,b,c) involves division. In the scalar case, when the divisor x is small, set 1/x = 1 in the equations marked by *.

A result of normalizing the lattice filter update algorithm is that the likelihood variable has been folded into the algorithm. The likelihood variable does not appear in the normalized update algorithm. The likelihood variable and all other unnormalized lattice filter parameters are recoverable form the parameters of the normalized lattice algorithm. The relationship between the normalized and unnormalized lattice parameters can be found in Friedlander (1982a, p. 863). The relationships between the normalized lattice parameters and the likelihood variable and the forward prediction error for the unnormalized lattice parameters follows.

$$\gamma^{c}_{p-1,T-1} = (1 - \gamma_{p-1,T-1}) = \prod_{i=0}^{p-1} (1 - \bar{r}_{i,T-1}\bar{r}_{i,T-1})$$

or

$$(1 - \gamma_{p,T-1}) = (1 - \gamma_{p-1,T-1})(1 - \bar{r}_{p,T-1}\bar{r}_{p,T-1}) \, .$$

$$R^{\varepsilon\,1/2}_{p,T} = S_T^{1/2} \prod_{i=1}^{p} (1 - K_{i,T}K_{i,T})^{1/2}$$

$$\varepsilon_{p,T} = (1 - \gamma_{p-1,T-1})^{1/2} R^{\varepsilon\,1/2}_{p,T} \, \bar{\varepsilon}_{p,T}$$

APPENDIX J

A FORTRAN IMPLEMENTATION OF THE NORMALIZED PRE-WINDOWED LEAST SQUARES LATTICE FILTER

The Normalized Pre-Windowed Least Squares Lattice Filter was implemented in two parts, a data structure holding the lattice parameters and the parameter update algorithm. Microsoft Fortran was used for the implementation. The lattice data structure is contained in a labeled common block. The lattice parameter update algorithm is contained in a subroutine. The parameter update algorithm is to be called for each new time step. The Fortran code for the lattice data structure and parameter update algorithm is given below. (This is a Fortan version of a program that was developed by Betsy Mates-Needham.)

```
****************************************************************************

NLATTICE.DST

THIS FILE DEFINES THE NORMALIZED PRE-WINDOWED LEAST SQUARES LATTICE
ALGORITHM DATA STRUCTURE. THE ALGORITHM WAS TAKEN FROM:
FRIEDLANDER, B., LATTICE FILTERS FOR ADAPTIVE PROCESSING, PROCEEDINGS
      OF THE IEEE, VOL. 70, NO.8, AUGUST 1982, pp. 845-846.
```

DEFINITIONS:

COMMON/NLATTICE/ - LABELED COMMON THAT CONTAINS THE LATTICE DATA STRUCTURE

NEERR - ARRAY CONTAINING NORMALIZED FORWARD PREDICTION ERRORS. EACH ELEMENT OF THE ARRAY CORRESPONDS TO THE COVARIANCE OF THE FORWARD ERROR FOR A PARTICULAR ORDER. NOTE THAT THERE IS AN OFFSET BETWEEN THE ARRAY INDEX AND ORDER. ARRAY INDEX 1 CORRESPONDS TO ORDER 0.

NRERR - ARRAY CONTAINING NORMALIZED BACKWARD PREDICTION ERRORS. EACH ELEMENT OF THE ARRAY CORRESPONDS TO THE COVARIANCE OF THE FORWARD ERROR FOR A PARTICULAR ORDER. NOTE THAT THERE IS AN OFFSET BETWEEN THE ARRAY INDEX AND ORDER. ARRAY INDEX 1 CORRESPONDS TO ORDER 0.

NRERRCOPY - ARRAY CONTAINING NORMALIZED BACKWARD PREDICTION ERRORS FOR THE PREVIOUS TIME STEP. EACH ELEMENT OF THE ARRAY CORRESPONDS TO THE COVARIANCE OF THE FORWARD ERROR FOR A PARTICULAR ORDER. NOTE THAT THERE IS AN OFFSET BETWEEN THE ARRAY INDEX AND ORDER. ARRAY INDEX 1 CORRESPONDS TO ORDER 0.

K - ARRAY CONTAINING NORMALIZED REFLECTION COEFFICIENTS. EACH ELEMENT OF THE ARRAY CORRESPONDS TO THE COVARIANCE OF THE FORWARD ERROR FOR A PARTICULAR ORDER. NOTE THAT THERE IS AN OFFSET BETWEEN THE ARRAY INDEX AND ORDER. ARRAY INDEX 1 CORRESPONDS TO ORDER 0.

S - ESTIMATED COVARIANCE OF THE DATA SEQUENCE.

(NOTE: INDEX 1 CORRESPONDS TO THE ZEROTH ORDER. THIS INCONVENIENT INDEXING METHOD IS DUE TO LIMITATION OF THE FORTRAN COMPILER BEING USED.)

```
************************************************************************

      REAL NEERR(10),NRERR(10), NRERRCOPY(10), K(10), S

      COMMON/NLATTICE/ NEERR,NRERR,NRERRCOPY,K,S

************************************************************************
```

```
      SUBROUTINE NUPDATELATTICE(DATA,ORDER,WEIGHT,TIME)

C*****************************************************************************

C     SUBROUTINE NUPDATELATTICE

C     THIS SUBROUTINE UPDATES THE NORMALIZED LEAST SQUARES LATTICE DATA
C     STRUCTURE FOR A NEW DATA POINT IN A INPUT DATA SEQUENCE. THE UPDATE
C     ALGORITHM WAS TAKEN FROM:
C     FRIEDLANDER, B., LATTICE FILTERS FOR ADAPTIVE PROCESSING, PROCEEDINGS
C          OF THE IEEE, VOL. 70, NO.8 AUGUST 1982, pp 845-846.

C     INPUT:

C     COMMON/LATTICE/ - UNNORMALIZED LATTICE DATA STRUCTURE (SEE
C          LATTICE.DST IN APPENDIX C)
C     COMMON/NLATTICE/ - NORMALIZED LATTICE DATA STRUCTURE (SEE
C          NLATTICE.DST)
C     ORDER - MAXIMUM ORDER OF THE LATTICE FILTER.
C     WEIGHT - EXPONENTIAL WEIGHTING FACTOR FOR PAST DATA.
C     DATA - A DATA POINT FROM A DATA SEQUENCE.
C     TIME - CURRENT TIME STEP.

C     OUTPUT:

C     COMMON/LATTICE/ - UNNORMALIZED LATTICE DATA STRUCTURE (SEE
C          LATTICE.DST FROM APPENDIX C)
C     COMMON/NLATTICE/ - NORMALIZED LATTICE DATA STRUCTURE (SEE
C          NLATTICE.DST)

C*****************************************************************************

$INCLUDE: 'LATTICE.DST'
$INCLUDE: 'NLATTICE.DST'

      REAL DATA,WEIGHT,SQRRE,PRODUCT,F,INVF
      INTEGER TIME,ORDER,P
```

```
*   INITIALIZATION

IF ((ABS(S) .LT. .000001).AND.(ABS(DATA).LT. .000001)) THEN
    NEERR(1) = 0.0
    NRERR(1) = 0.0
ELSE
    S = WEIGHT*S + DATA*DATA
    NEERR(1) = DATA / SQRT(S)
    NRERR(1) = NEERR(1)
ENDIF


EERR(1) = DATA

PRODUCT = 1.0
LHOOD(1) = 1.0

DO 100 P = 1,MIN(ORDER,TIME)

    K(P+1) = INVF(K(P+1), NRERRCOPY(P), NEERR(P))
    NEERR(P+1) = F(NEERR(P),NRERRCOPY(P),K(P+1))
    NRERR(P+1) = F(NRERRCOPY(P), NEERR(P), K(P+1))


    * CALCULATING LIKELIHOOD VARIABLE AND UNNORMALIZED FOR-
    WARD PREDICTION ERROR
    * NOTE THAT THE FOLLOWING CALCULATIONS ARE NOT PART OF THE
    NORMALIZED LATTICE FILTER UPDATE ALGORITHM.

    LHOOD(P+1) = LHOOD(P)*(1 - NRERR(P)*NRERR(P))
    IF (LHOOD(P+1) .LT. 0.0) THEN
        LHOOD(P+1) = 0.0
    ENDIF
    PRODUCT   = PRODUCT*SQRT(1 - K(P+1)*K(P+1))
    SQRRE     = SQRT(S)*PRODUCT
    EERR(P+1) = SQRT(LHOODCOPY(P+1))*SQRRE*NEERR(P+1)

100 CONTINUE

DO 200 P = 1,MAXORDER

    NRERRCOPY(P) = NRERR(P)
```

```
          LHOODCOPY(P) = LHOOD(P)

200     CONTINUE
        RETURN
        END



************************************************************************


        REAL FUNCTION F(A,B,C)


        IF (C .GT. 1.0) THEN
           C = 1.0
        ELSE IF (C .LT. -1.0) THEN
           C = -1.0
        ENDIF

        IF (B .GT. 1.0) THEN
           B = 1.0
        ELSE IF (B .LT. -1.0) THEN
           B = -1.0
        ENDIF

        X1 = SQRT(1.0 - C*C)
        IF (X1 .LT. .000001) THEN
           INVX1 = 1.0
        ELSE
           INVX1 = 1.0/X1
        ENDIF

        X2 = SQRT(1.0 - B*B)
        IF (X2 .LT. .000001) THEN
           INVX2 = 1.0
        ELSE
           INVX2 = 1.0/X2
        ENDIF
```

```
F = INVX1*(A - C*B)*INVX2

RETURN
END
```

```
****************************************************************************

REAL FUNCTION INVF(A,B,C)

REAL A,B,C

IF (C .GT. 1.0) THEN
   C = 1.0
ELSE IF (C .LT. -1.0) THEN
   C = -1.0
ENDIF

IF (B .GT. 1.0) THEN
   B = 1.0
ELSE IF (B .LT. -1.0) THEN
   B = -1.0
ENDIF

RETURN
END

****************************************************************************
```

APPENDIX K

REVIEW OF THE DEVELOPMENT OF THE MICROWAVE VITAL LIFE SIGNS MONITOR

The use of a microwave device in the measurement of human heart rate can be found in Byrne, Flynn, Zapp, and Siegel (1986), Byrne and Siegel (1985), Byrne, Zapp, Flynn, and Siegel (1985), Hoshal, Ivkovich, Siegel, and Zapp (1984), Hoshal and Siegel (1986), Hoshal, Siegel, and Zapp (1984), Lin, Kiernicki, Kiernicki, and Wollschlaeger (1979), and Popovic, Chan, and Lin (1984). The research presented in this thesis is an extension of the work done in developing a heart rate estimation method for the Michigan State University Biomedical Signal Processing Laboratory's microwave vital life signs monitor (Byrne et al., 1986; Byrne & Siegel, 1985; Byrne et al., 1985; Hoshal, Ivkovich, et al., 1984; Hoshal & Siegel, 1986; Hoshal, Siegel, et al., 1984). This appendix will review the history of the development of heart rate measurement techniques for the Michigan State University unit.

The First Michigan State University Microwave Vital Life Signs Monitor

The first version of the Michigan State University microwave vital life signs monitor was used by Byrne, Flynn, Zapp, and Siegel (1986), Byrne and Siegel (1985), Byrne, Zapp, Flynn, and Siegel (1985), Hoshal, Ivkovich, Siegel, and Zapp (1984), Hoshal and Siegel (1986) and

Hoshal, Siegel, and Zapp (1984). Figure K1 is a block diagram of the device. A description of the device's operation was found in Hoshal, Ivkovich, *etal*. (1984) and Hoshal, Siegel, *etal*. (1984). In the monitor, a portable homodyne transceiver system is responsible for transmitting a low-level microwave signal and detecting Doppler shifts in the returned signal. The microwave transceiver emits a 10.5 GHz continuous wave at a level of a few milliwatts (more recent versions of the instrument use pulsed transmitters). The returns of the microwave signal supply an analog signal of only a few microvolts to the Doppler shift detector. After Doppler shift detection, the low-level analog signal is sent through an amplifier that provides 60dB to 80dB of signal amplification. After signal amplification, the analog signal is filtered with a bandpass filter. The band of the filter was placed at 1-30 Hz. The selection of the 30 Hz cutoff was based on the spectral analysis of signals resulting from reflections of microwave signals off the chest walls of human subjects. There were no significant spectral components of the microwave heartbeat signals past 30 Hz (Hoshal, Siegel, & Zapp, 1984). The low end cutoff of 1 Hz is used to eliminate any DC component in the signal and minimize breathing effects (M. Siegel, personal communication, 1988).

The amplified and filtered analog signal is sampled by an eight-bit analog to digital converter. The sampling rate varied from 96 to 128 samples per second in the above studies. The final destination of the digitized microwave signal is a microprocessor. The final heart rate estimation algorithms will reside in the microprocessor unit.

In order to evaluate the success of any heart rate measurement method, a reference of the actual heartbeat activity is needed. A heartbeat reference signal was successfully obtained from an in-house designed unit that measures body surface potential between the hands of a human subject. The output of the device closely resembles an EKG signal. Hand potential signals were simultaneously recorded when microwave heartbeat measurements were taken.

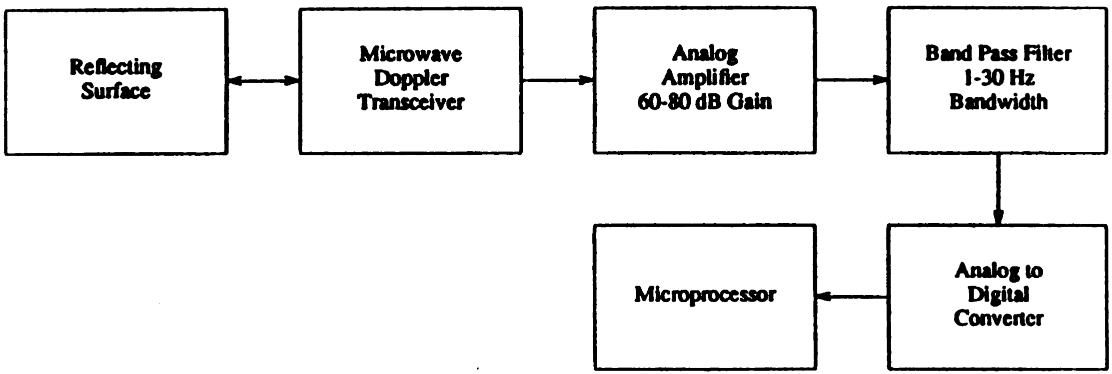


Figure K1. The first Michigan State University microwave vital life signs monitor.

Review of the Development of a Heart Rate Estimation Method for the Michigan State University Microwave Vital Life Signs Monitor

Peak detection.

Peak detection was the first method considered in the development of a heart rate estimation technique. In an uncluttered signal, the microwave measurements of a heartbeat resembles a heartbeat occurrence in an EKG. Large peaks in the microwave signal correlate with the occurrences of heartbeats. The large peaks can be located with peak detection.

Peak detection is effective for only a restricted set of operating conditions. The subject must be rested and breathing regularly during the recording of the microwave measurements. The transceiver must be placed at only short distances away from the chest wall of the subject. There must be little interference from breathing or background movement in the Doppler shifted encoded heartbeat signal. Under realistic operating conditions, the heartbeat signal may be obscured by background noise and clutter. Peak detection techniques applied to the microwave heartbeat signal are unreliable for realistic operating conditions (Hoshal, Ivkovich, Siegel, & Zapp, 1984; Hoshal, Siegel, & Zapp, 1984; Byrne & Siegel, 1985).

Correlation Techniques.

The next stage of the development of a heart rate estimation technique was based on utilizing the periodic nature of heartbeat occurrences in the microwave signal. Peak detection failed because of the high level of clutter in the microwave signal. Hoshal, Ivkovich, Siegel, and Zapp (1984) and Hoshal, Siegel and Zapp (1984) posed the following argument: If correlation techniques are useful in detecting periodic signals that are completely obscured by random noise, then correlation techniques may be useful in extracting the heartbeat signal from the microwave measurements. Autocorrelation was performed on the Michigan State University monitor microwave heartbeat signal by Hoshal, Ivkovich, *etal*. (1984) and Hoshal, Siegel, *etal*. (1984). Lin, Kiernicki, Kiernicki, and Wollschlaeger (1979) and Popovic, Chan, and Lin (1984) also used autocorrelation to estimate heart rate from a microwave heartbeat signal. Hoshal, Ivkovich, *etal*. (1984) and Hoshal, Siegel, *etal*. (1984) showed that autocorrelation could be used to accurately measure heart rate, but the set of operating conditions used to test the autocorrelation techniques was limited. A number of problems were encountered when heart rate estimation methods using autocorrelation were more rigorously tested.

The ability of autocorrelation methods to separate a signal from obscuring noise is dependent on the signal being periodic. Human heartbeats are pseudo periodic events. The time period between heartbeats may not be constant (Byrne & Siegel, 1985; Hoshal & Siegel, 1986). The less the heartbeats are periodic the more the autocorrelation peaks broaden. An accurate estimation of the heart rate cannot be obtained from the broadened autocorrelation peaks.

The length of the periods between heartbeats can change abruptly. The autocorrelation time window length must be restricted to the duration of a few heartbeats in order to track abrupt changes in heart rate (Byrne & Siegel, 1985; Hoshal & Siegel, 1986). When the periods between heartbeats are regular, a longer autocorrelation time window is desirable since it would result in more accurate estimates of autocorrelation peak locations (Byrne & Siegel, 1985). A trade off must be made in chosing a time window length if autocorrelation is to be used in estimating heart rate from the microwave signal. This is a classical time-frequency resolution problem.

It was also found that the signature of a heartbeat occurrence in the microwave signal can change not only from person to person but from heartbeat to heartbeat (Byrne & Siegel, 1985). Autocorrelation techniques depend on repeated behavior. If the same pattern is not repeated in the microwave signal for each occurrence of a heartbeat, the effectiveness of autocorrelation as a heartbeat signal detector will be limited.

The ability of autocorrelation to extract the heartbeat signal from the microwave measurements is further underminded by the presence of periodic background components (Byrne & Siegel, 1985). The most dominant periodic component is breathing. It is difficult to filter out breathing because there is no prior knowledge of a subject's breathing rate during the microwave measurement of the subject's heart rate. Because the breathing rate may be close to the heart rate and many times larger in amplitude, the problem of removing the breathing component is compounded.

Variations in the heartbeat signal have limited the success of using autocorrelation to estimate heart rate from the microwave signal. Hoshal and Siegel (1986) observed that variations in the level of the microwave signal clutter also effected the performance of autocorrelation. Autocorrelation was unreliable in cases of low signal-to-noise ratios (SNR) or high clutter level environments (Hoshal & Siegel, 1986). Experimental measurements showed that obtaining a sufficiently high SNR cannot be done consistently. The SNR was strongly affected by the positioning of the microwave transceiver over the body. The unpredictable rate and strength of the breathing motion also affected their ability to obtain a consistent SNR.

Hoshal and Siegel (1986) postulate that signal and clutter variations will become an even bigger problem when the microwave monitor is to be used in the field. The heart rate estimation technique must be able to contend with uncontrollable background clutter and pathological heart conditions. Hoshal and Siegel call for a robust signal processing methodology. A methodology that can make a reasonable estimate of the heart rate from the microwave signal despite the possible variations in the heartbeat signal and background noise that might be encountered.

The Hoshal and Siegel Stochastic Model of the Microwave Heartbeat Signal

The approach Hoshal and Siegel (1986) took to develop a robust heart rate estimation method was to formulate a stochastic model of the microwave heartbeat signal in order to gain knowledge about the statistics of the microwave signal. The knowledge gained was then used to aid in the development of an optimal processing technique.

Hoshal and Siegel model the microwave heartbeat signal as

$$y(t) = x(t) * h(t), \tag{K1}$$

where * denotes convolution. $y(t)$ is the microwave heartbeat signal. $x(t)$ is a pseudo periodic impulse train defined by

$$x(t) = \delta(t-T_0) + \delta(t-T_0-T_1) + \ldots + \delta(t-\sum_{i=0}^{n} T_i) + \ldots, \tag{K2}$$

where T_i is a time series formed from successive beat-to-beat periods. $\delta(t)$ is the has a value of ∞ for $t = 0$. Otherwise, $\delta(t)$ is zero. $h(t)$ represents the time domain response characteristics of a single heartbeat cycle.

The beat-to-beat period sequence, T_i, is modeled as a 4th order autoregressive process. The parameters of the T_i model were based on time intervals between heartbeat occurrences in the hand potential reference signals. A six pole, six zero pole-zero model is used for $h(t)$. The parameter estimation for $h(t)$ was based on microwave signals taken from 10 subjects. Background noise was minimal during the recording of the signals. The subjects were lying on their backs while the measurements were taken. Hoshal and Siegel (1986) do not state whether the monitor was placed directly on the chest wall or at some distance from the chest wall of the subjects.

The model was then used to estimate the power spectral density of the microwave signal. Microwave signals were simulated for various means and variances of the model parameters. The power spectral density of the simulated microwave signals were obtained. Distinct harmonic peaks were seen in the power spectrum of each simulated microwave heartbeat signal, even for the signals with the worst cases of the parameters variances.

The time varying nature of a human's heart rate and the harmonic peaks in the power spectral density of the simulated microwave signals suggested to Hoshal and Siegel that adaptive comb filtering may be an appropriate technique to estimate heart rate. As described in Hoshal and Siegel (1986), the adaptive comb filter searches the components of the input signal spectrum for a best fit to a specified number of harmonically related signal components. Nonharmonic components are attenuated. The best fit fundamental frequency is the estimate of the heart rate.

Results of preliminary tests on the adaptive comb filter's ability to estimate heart rate are given in Hoshal and Siegel, (1986). The adaptive comb filter was applied to simulated and actual microwave data. The simulated data consisted of a series of microwave heartbeats generated by the Hoshal and Siegel model added to band-limited white noise. The real microwave data was taken under the same conditions as the microwave data used to estimate the Hoshal and Siegel model parameters. The adaptive comb filter gave accurate estimates of the heart rates for both simulated and real data.

Although adaptive comb filtering shows promise as a method for estimating heart rate from the microwave signal, further investigation is needed. The Hoshal and Siegel model is based on data recorded under ideal conditions. The model needs to be expanded to include pathological heartbeat behavior and the affects of breathing and background clutter (Hoshal & Siegel, 1986). The ability of the comb filter to adapt to abrupt changes in heart rate needs to be investigated. It must be determine that the adaptive comb filter technique can give accurate heart rate estimates for microwave heartbeat signals cluttered by breathing and background movements. The robustness of the adaptive comb filter has yet to be proven.

The Byrne and Siegel Stochastic Model of the Microwave Heartbeat Signal.

The approach that Byrne and Siegel (1985) took to find a robust heart rate estimator is similar to approach taken by Hoshal and Siegel (1986). Byrne and Siegel postulated a model for the microwave heartbeat signal and then used the model to apply an adaptive filter in the estimation of heart rate. The Byrne and Siegel model is similar to the Hoshal and Siegel model but the choice of adaptive filtering is different.

Byrne and Siegel (1985) modeled the microwave heartbeat signal as the output of an all-pole filter that is excited by a train of impulses added to white noise. The Byrne and Siegel model is shown in Equation K3.

$$y(t) = [x(t) + w(t)] * h(t), \tag{K3}$$

where * denotes convolution. $y(t)$ is the microwave heartbeat signal. $x(t)$ is the pseudo periodic train of impulses. Equation K2 of the Hoshal and Siegel (1986) model can be used to define $x(t)$ of the Byrne and Siegel model. $w(t)$ is a band-limited white process. $h(t)$ is the impulse response of the all-pole filter. The response of the all-pole filter excited by one impulse should resemble a microwave signal heartbeat. This model differed from the Hoshal and Siegel model in two ways. The Hoshal and Siegel model used a pole-zero filter where the Byrne and Siegel model uses an all-pole filter. Secondly, the Byrne and Siegel model includes white noise as a component in the excitation process of the model.

The primary motivation behind using the Byrne and Siegel (1985) model for the microwave heartbeat signal was the success of applying a similar model to the problem of detecting pitch pulses in voiced speech. The particular pitch detection technique that prompted Byrne and Siegel to adopt the model in Equation K3 was developed by Lee and Morf (1980). Voiced sounds such as vowel sounds can be modeled as the output of an all-pole filter excited by a pseudo periodic train of impulses. The impulse train models the pitch pulses. The all-pole filter of the speech model represents the vocal tract. In speech analysis, it is of interest to determine the period between the pitch pulses. Linear prediction can be used to inverse the all-pole filter's response and recover the pseudo impulse train that excited the all-pole filter. The recovered impulses appear as large prediction errors at the output of the linear predictor. (Appendix L reviews the relationship between the Byrne and Siegel model and linear prediction.) For different sounds, the vocal tract will take on different configurations. In order to inverse the effects of the vocal tract on the pitch pulses by linear prediction, the configuration of the vocal tract must be determined. The proper configuration of the all-pole filter model might not be known or might change within a speech process. Adaptive linear prediction is used to determine the unknown configuration of the vocal tract model.

Byrne and Siegel (1985) modeled the occurrence of heartbeats as a pseudo periodic impulse train. The chest wall, microwave, microwave channel and monitoring unit are modeled with an all-pole filter. If the Byrne and Siegel model is valid for the microwave heartbeat signals, linear prediction can be used to recover the heartbeat impulse train. Like the speech process, the system the heartbeat impulse train excites might not be known or might change in time. Assuming their model is valid, Byrne and Siegel used adaptive linear prediction to determine the configuration of the system model. Once the heartbeat impulses are recovered through adaptive linear prediction, Byrne and Siegel hoped to estimate the instantaneous heart rate by measuring the period between consecutive impulses.

In Lee and Morf (1980), the recovery of pitch impulses was enhanced by the use of a parameter of the particular adaptive linear predictor they used. The parameter is related to the log-likelihood function of the speech process input to the adaptive linear predictor. The parameter is a measure of the unexpectedness of the most recent data points of the speech process (Friedlander, 1982a). Sudden large changes in this variable were good indicators of the occurrence of a pitch pulse. Byrne and Siegel used this parameter in the same way to enhance the recovery of heartbeat occurrences.

If the Byrne and Siegel (1985) method of estimating heart rate is valid for microwave measurements, the primary advantage of the method over autocorrelation is that the detection of the heartbeats is not dependent on the periodicity of the heartbeat. With the Byrne and Siegel method, the occurrence of a heartbeat would be recognized by the occurrence of a special event at the output of an adaptive linear predictor: the presence of a large prediction error and an abrupt large change in the likelihood parameter.

The Byrne and Siegel (1985) heartbeat detection technique would have a computational advantage over autocorrelation. Byrne and Siegel (1985) experimented with a number of different adaptive linear predictors and found the best results to come from a normalized least-squares lattice filter, a normalized version of the adaptive linear predictor used by Lee and Morf (1980). The filter is a recursive algorithm. The parameters of the adaptive lattice filter are updated for every new data sample input to the filter. Autocorrelation processing requires blocks of data, therefore there is a time delay between estimates of the heart rate. The lattice filter structure allows for updates of heart rate estimation with every new input data sample.

The performance of the Byrne and Siegel (1985) heartbeat detection technique is impressive. Microwave signals obtained from subjects lying flat with the microwave monitor mounted directly on the their chests were processed. Byrne and Siegel obtained large prediction errors and large changes in the likelihood parameter during the occurrences of heartbeats. The exact timing of heartbeat occurrences was determined by hand unit reference signals. After the errors were masked by the derivative of the likelihood parameter, peak detection was used to determine the location of the heartbeats. The heartbeat signal was successfully recovered from these microwave signals. Note that autocorrelation could have been used to estimate the heart rate because of the regularity of the data and the lack of clutter.

In order to more rigorously test the Byrne and Siegel heartbeat detection method, adaptive linear prediction was applied to microwave heartbeat signals taken from subjects placed three feet from the microwave monitor. The subjects were seated and had exercised. Having the subjects sitting is considered to be a more hostile condition for heartbeat detection compared to lying down. In the sitting position, it is felt that the heart impinges the chest wall to a lesser degree than the if the subject is lying down (M. Siegel, personal communication, 1988). The heartbeat signal was obscured in these measurements. Unlike the signals recorded for subjects lying down, autocorrelation failed to give accurate heart rate estimates. The use of the normalized adaptive lattice filter prediction error and likelihood parameter gave consistently accurate estimates of the instantaneous heart rate of the subjects.

Current Interest in the Development of a Heart Rate Estimation Technique

The current interest in the development of a technique to estimate heart rate for the microwave vital life signs monitor is to formulate a real-time implementations of the most promising heart rate estimation techniques. The real-time implementations would be used on board the heart rate monitor. The heart rate estimation techniques developed by Hoshal and Siegel (1986) and Byrne and Siegel (1985) were implemented and tested independent of the monitor. Recorded data files were used. The initial purpose of this thesis research was to develop a real-time implementation of Byrne and Siegel adaptive least squares lattice filter estimation method.

Although Byrne and Siegel (1985) showed that the adaptive lattice filter technique worked well under adverse conditions, the technique had not been fully tested. The technique was tested with only a few data files and the results shown in Byrne and Siegel (1985) were of cases in which the technique worked very well (M. Siegel, personal communication, 1988). Before a great deal of effort was expended in developing a real-time implementation of the Byrne and Siegel technique, more extensive off-line testing of the algorithm was performed.

A number of problems were encountered in the attempt to repeat the results of Byrne and Siegel (1985). The source of these problems was traced to differences in the character of current microwave heartbeat signals and the data used in Byrne and Siegel (1985). The differences might be the result of two actions. First, a number of modifications have been made to the microwave unit since the Byrne and Siegel study. Second, the standard testing position of the microwave monitor and subject has changed.

The Modified Michigan State University Microwave Vital Life Signs Monitor.

Figure K2 shows a block diagram of the current microwave vital life signs monitor. Four major modifications were made. All the changes were made to the analog signal processing section of the monitor. The transmitted microwave signal was changed from a continuous wave to a pulsed microwave. This modification was made to improve the safety of subjects during exposure of the microwave transmission and to minimize power consumption (M. Siegel, personal communication, 1988). A logarithmic amplifier was added to increase the dynamic range and sensitivity of the microwave transceiver. The logarithmic amplifier increases the systems sensitivity to small signals while large signals are not allowed to saturate the system. An automatic gain control unit was added so that the input to the data processing section of the monitor would have an even level. The band-pass filter was changed to a switched capacitor filter. This modification allows the microprocessor unit of the monitor to control the character of the band of the switched capacitor filter during operation of the monitor.

The cut-off frequencies of the switched capacitor filter remained constant during this thesis research. The low frequency cut-off was 4 Hz and the high frequency cut-off was 15Hz. The 4 Hz cut-off was chosen to filter out signal components related to breathing and still allow harmonics of the heartbeat signal to pass. It is believed that most breathing components are found at or below 4 Hz (M. Siegel, personal communication, 1988). The 15 Hz cut-off was used to reduce noise. The latest spectrum analysis of the microwave heartbeat signal show that there were no significant heartbeat signal components above 15 Hz (M. Siegel, personal communication, 1988).

The current standard positioning of the monitor and the subject are different than the positioning used in Byrne and Siegel (1985). Current microwave data are recorded with the subject

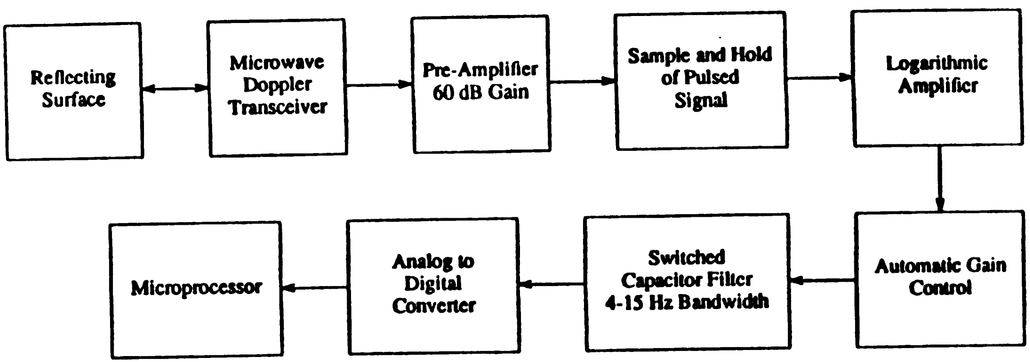


Figure K2. The modified Michigan State University microwave vital life signs monitor.

sitting. The monitor is placed six inches from the subjects chest wall. The monitor is placed slightly to the left of the center of the chest wall. The subjects are sitting rather than lying down.

APPENDIX L

REVIEW OF THE RELATIONSHIP BETWEEN AUTOREGRESSIVE PROCESS SYNTHESIS AND ADAPTIVE LINEAR PREDICTION

An autoregressive (AR) process is modeled as

$$y(n) = \sum_{k=1}^{M} a_k y(n-k) + w(n), \tag{L1}$$

where $y(n)$ is the AR process, the a_k's are the AR model parameters, $w(n)$ is a white process, and M is the order of the model. A sample of an AR time-series can be expressed as a linear combination of past samples plus a sample from a white process. The number of past samples in the linear combination is the order of the AR process. The time interval between samples is constant.

Equation L2 shows that the AR process can be modeled as the output of an all-pole filter excited by a band-limited white process.

$$Y(z) = \left[\frac{1}{1 - \sum_{k=1}^{M} a_k z^{-k}} \right] W(z). \tag{L2}$$

The model in (L2) was formed by taking the z-transform of (L1) and treating W(z) as the input to a system and Y(z) as the output of the same system. A fundamental goal of AR model analysis is to determine the parameters of the all-pole filter. Linear prediction is can used to estimate the coefficients of the AR model all-pole filter.

Linear prediction estimates the next data sample of an AR process by a linear combination of past data samples.

$$\hat{y}(n) = \sum_{k=1}^{M} b_k y(n-k), \tag{L3}$$

where $\hat{y}(n)$ estimates $y(n)$ and b_k is a linear prediction coefficient. The prediction error is defined in (L4).

$$e(n) = y(n) - \sum_{k=1}^{M} b_k y(n-k), \tag{L4}$$

where $e(n)$ is the prediction error. By taking the z-transform of the error equation and treating the prediction error as the output of a system and the AR process as the input of the same system, (L5) shows that linear prediction can be viewed as the inverse operation of AR process synthesis (Haykin, 1984).

$$E(z) = \left[1 - \sum_{k=1}^{M} b_k z^{-k}\right] Y(z) \tag{L5}$$

Linear prediction deconvolves the AR process. If the prediction error sequence is viewed as the output of linear prediction, then applying linear prediction to an AR process is the same as passing the AR process through an all-zero filter. If the prediction coefficients are the same as the AR model parameters, then the prediction error is the same as the white process input of the AR model all-pole filter. The linear prediction coefficients can be used to estimate the AR model parameters.

How are the linear prediction coefficients found? If the past values of an AR process and the relationship between those past values are known, the only thing the one cannot predict about the next value of the process is the sample from the white process. The prediction error will contain the white process sample. If the linear predictor can be used to extract the part of the process sample that is correlated with the past process samples, the prediction error will be minimal.

If the statistics of the AR process being analyzed are known, a way to optimize the the selection of linear prediction coefficients is by minimizing the mean of the squared prediction error, $E\{e^2(n)\}$. The parameters of the predictor are uniquely determined by the second-order statistics of the process. The Yule-Walker equations give a linear relationship between the predictor parameters and the autocorrelation coefficients, $\{R_i, i=0,...M\}$ where $R_i = E\{y(n)y(n-i)\}$. The optimal mean squared error predictor or the least squares predictor can be obtained by solving the Yule-Walker equations.

In most applications, the statistics of the process are not known and must be estimated from data. Often, the process statistics are time-varying. In order to track the changing statistics of a non-stationary process, estimates of the second-order statistics and computations of the predictor coefficients need to be continually updated. The problem of predicting a time-series without prior knowledge of its statistics is called adaptive prediction (Friedlander, 1982a).

When the second-order statistics of the process being predicted are known, estimation of the least squares predictor is a well defined problem. A well defined problem is also possible for the estimation of least squares prediction parameters when all the information that is known about the process is a finite number of data points, $\{y(n)\}$ where $n=1,2,...N$. The problem as defined in Friedlander (1981) is to fit the observed data to a linear model by choosing prediction coefficients, $\hat{\Theta}_i$, that minimize the sum of the squared prediction errors,

$$SSE = \sum_{n=1}^{N} e^2(n), \tag{L6}$$

where

$$e(n) = y(n) + \sum_{i=1}^{M} \hat{\Theta}_i y(n-i). \tag{L7}$$

The estimates of the coefficients are given by the homogeneous solution to the equations in (L8).

$$\begin{bmatrix} e(1) \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ e(N) \end{bmatrix} = \begin{bmatrix} y(1) \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ y(N) \end{bmatrix} + \begin{bmatrix} y(0) & & 0 \\ \cdot & \cdot & \\ \cdot & & \cdot \\ \cdot & & y(0) \\ \cdot & & \cdot \\ y(N-1) & \cdot\ \cdot & y(N-M) \end{bmatrix} \cdot \begin{bmatrix} \hat{\Theta}_1 \\ \cdot \\ \cdot \\ \hat{\Theta}_M \end{bmatrix} \tag{L8}$$

(L8) can be more compactly written as

$$e = y + Y\hat{\Theta}, \tag{L9}$$

where

$$e = \begin{bmatrix} e(1) \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ e(N) \end{bmatrix}, \qquad y = \begin{bmatrix} y(1) \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ y(N) \end{bmatrix},$$

$$Y = \begin{bmatrix} y(0) & & 0 \\ \cdot & \cdot & \\ \cdot & \cdot & y(0) \\ \cdot & & \cdot \\ \cdot & & \cdot \\ y(N-1) & \cdot\ \cdot & y(N-M) \end{bmatrix}, \quad \text{and} \quad \hat{\Theta} = \begin{bmatrix} \hat{\Theta}_1 \\ \cdot \\ \cdot \\ \cdot \\ \hat{\Theta}_M \end{bmatrix}.$$

The solution of (L8) is given by

$$\hat{\Theta} = \hat{R}^{-1} Y^T y, \tag{L10}$$

where Y^T is the transpose of Y and $\hat{R}$ is the sample covariance matrix.

$$\hat{R} = Y^T Y \tag{L11}$$

The equations that provide the solution to the problem of estimating the predictor coefficients of a process with unknown statistics has the same form as the Yule-Walker equations, which were derived for process with known statistics (Friedlander, 1982a).

There are a number of efficient computational procedures for solving these equations. The adaptive least squares lattice filter used by Byrne and Siegel (1985) is an example. The usefulness of the relationship between AR modeling and adaptive linear prediction will be illustrated in Appendix M by showing how this relationship has been used in the analysis of speech processes.

APPENDIX M

ILLUSTRATING THE USE OF ADAPTIVE LINEAR PREDICTION TO EXTRACT IMPULSES FROM PROCESSES USING SPEECH PROCESSES AS AN EXAMPLE

A simplified model for speech production is shown in Figure M1. The model consists of an all-pole filter that is excited by either a quasi-periodic train of impulses or a white noise source (Makhoul, 1975). Voiced sounds such as vowels are generated from nearly periodic impulse sources. The impulse train represents a series of pitch pulses. The impulses are spaced at a fundamental period known as the pitch period. The white process produces the unvoiced sounds such as the f in fish. The probability distribution of the white process does not appear to be critical (Haykin, 1984, chap. 1). The all-pole filter models the vocal tract. The identity of the sound produced by both sources is determined by the parameters of the all-pole filter (Makhoul, 1975).

In speech recognition and synthesis, it is of interest to determine the character of the individual sounds that make up a speech process. If the above model is used, the type of input source that produces the sound must be known. For voiced sound, the pitch period of the impulse train must be determined. The parameters of the all-pole filter are needed for both voiced and unvoiced sounds. Therefore, the objectives in analyzing a speech process is to estimate the model parameters and recover the input process.

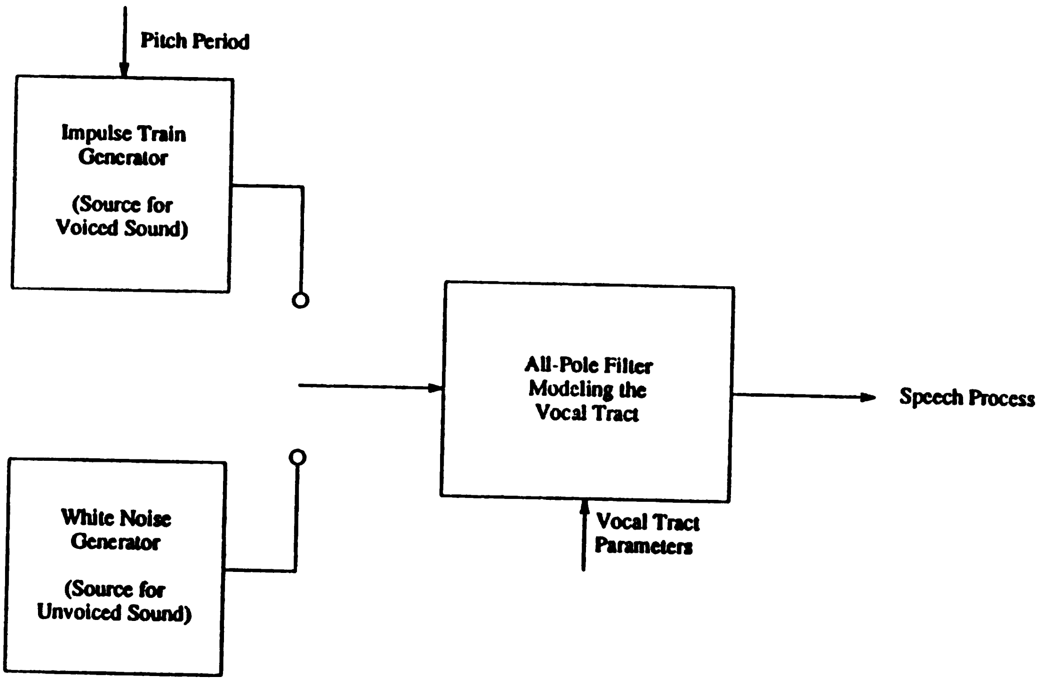


Figure M1. Block diagram of simplified model for speech production.

Linear prediction is used in the analysis of speech processes. Parameter estimation performed through least squares linear prediction works well provided the input to the all-pole system is a zero mean white process. Linear prediction can be used to deconvolve a process that is the output of an all-pole filter that has been excited by a white process. The white excitation process is recoverable from the prediction error. For the analysis of sounds produced by a white input, the constraints on the use of least squares linear prediction present no problem. But, the periodic impulse source that generates voiced sounds is not white. Estimates of model parameters may be biased and deconvolution may be imperfect for non-white input processes. For example, if an input is coherent, the input may not be recoverable from the prediction error. The model parameters would absorb the correlation information of the input process. The least squares linear predictor would produce as nearly as possible a white prediction error sequence.

If the non-white input is known, then it is possible to unbias the estimate of the model parameters (Friedlander, 1981). In speech analysis, the input to the all-pole model may not be known apriori. In certain situations, it may be possible to estimate a non-white input from the prediction error sequence. In particular, this may be true for the case where the input is an impulse train as in speech processes (Friedlander, 1981).

Imagine that an all-pole filter of known parameters was excited by a single impulse. A linear predictor with a configuration that inverses the operation of the all-pole filter would be able to perfectly predict the impulse response of the all-pole filter except for the first non-zero value of the response (see Figure M2). This initial non-zero value would show up in the prediction error (Makhoul, 1975). Similarly, a large prediction error is a good indicator of the occurrence of an impulse exciting the all-pole speech model.

Imagine that the configuration of the above all-pole filter was not known. The parameters of the all-pole filter may be obtained from the impulse response of the filter. The parameters of an unknown all-pole filter can be estimated when the autocorrelation coefficients are known for

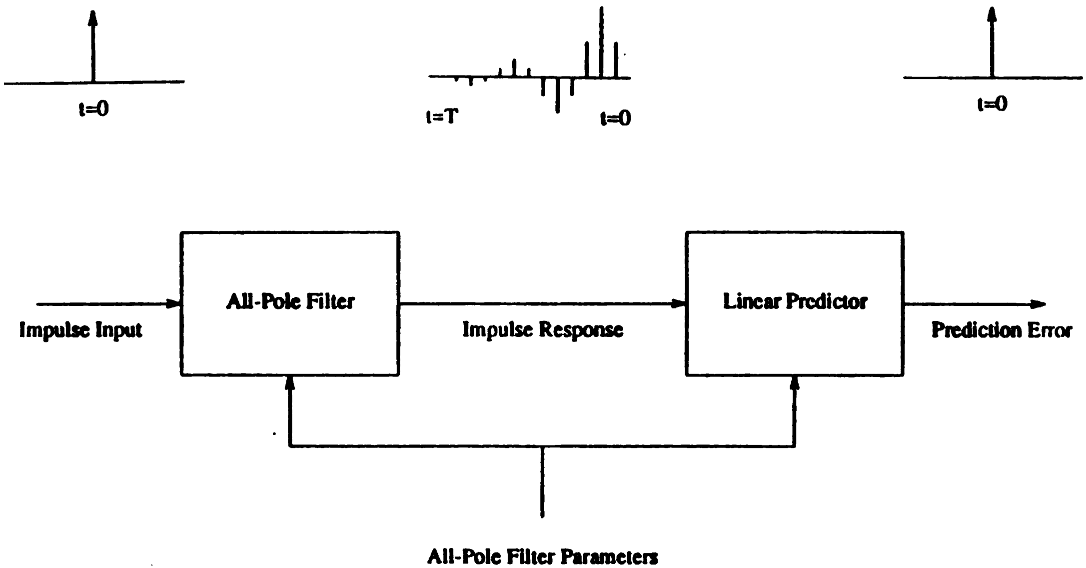


Figure M2. Deconvolution of the impulse response of an all pole filter by linear prediction.

the output of an all pole filter excited by a white process. Makhoul (1975) shows how the relationship linking the autocorrelation coefficients of the output of an all-pole filter are the same for both the input of a single impulse or a white process. This result is expected because both a deterministic impulse and a white noise process have identically flat spectra. Makhoul observes that the usefulness of this dualism between a deterministic impulse and statistical white noise is shown in the modeling the speech processes.

It might appear that the pitch pulses of a speech process could be located by large prediction errors, but there are some problems with this method. A signal impulse is a noncorrelated process were as an impulse train is correlated. The linear prediction estimates of the speech process may be biased. The linear predictor may not perfectly deconvolve the speech process. This problem has been studied in the area of speech analysis. Friedlander (1981) shows how a particular linear predictor, a least squares lattice filter, can be modified such that its predictions are not biased when the linear predictor is used to deconvolve the output of an all-pole filter that has been excited by an impulse train.

Another problem in relying on the presence of large prediction errors to indicate the location of pitch pulse in a speech process is that the system that produces the speech process must be minimum phase. The all-pole filter of the speech model has all of its poles and zeros inside the unit circle. If linear prediction is used to inverse the operation of a system that is not minimum phase, the prediction error will probably not resemble the process that excited the system.

APPENDIX N

THE UNNORMALIZED PRE-WINDOWED LEAST SQUARES LATTICE FILTER

The Unnormalized Pre-Windowed Least Squares Lattice Filter is the same adaptive least squares lattice filter used by Lee and Morf (1980) in their pitch pulse detector. The least squares lattice algorithm is based on the Levinson-Durbin recursive method of computing the solution to the Yule-Walker equations. The Yule-Walker equations provide a solution to the problem of estimating linear prediction coefficients for processes with known statistics. Haykin (1984), Friedlander (1982a), and Lee, Morf, and Friedlander (1981) show how the least squares lattice filter is derived by applying the Levinson-Durbin method to the problem of estimating linear prediction coefficients for processes with unknown statistics. Pre-windowed implies that it was assumed that the input processes to the lattice filter is zero prior to $t = 0$. The procedure of estimating linear prediction coefficients for processes with unknown statistics is usually done by minimizing the sum of the squared prediction errors and is called least squares linear prediction.

Operating on a process with linear prediction can be viewed as being the same as passing the process through an finite impulse response (FIR) filter or all-zero filter. The output of the filter is the prediction error. It is usually assumed that a linear predictor is implemented in the direct (or tapped-delay-line) form (Friedlander, 1982a). Figure N1 shows a direct realization of a least squares linear predictor. The direct realization coefficients, A_i's, are estimated by the $\hat{\Theta}$'s of

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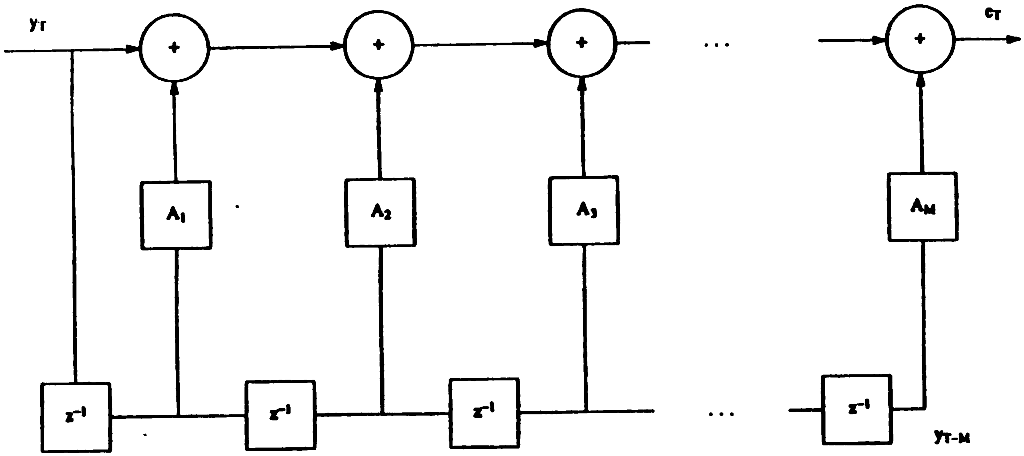

Figure N1. Direct realization of an order M least squares linear predictor.

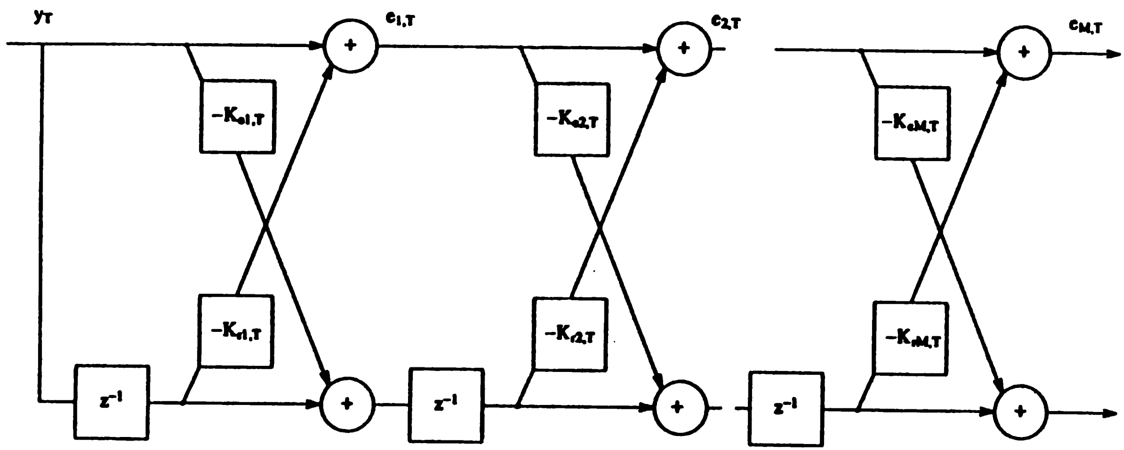

Figure N2. Lattice Realization of an order M least squares linear predictor.

(L8). The $\hat{\Theta}$'s are the solutions to the least squares linear prediction problem for processes with unknown statistics. The structure of the Unnormalized Pre-windowed Least Squares Lattice Filter is shown in Figure N2. The K_i's of the lattice implementation are called the reflection coefficients. Appendix E gives the algorithm that is used to update the parameters of the lattice filter. The direct realization of the least squares linear predictor and the least squares lattice filter are mathematically equivalent. Values for the direct realization coefficients can be derived from the lattice parameters. Appendix F gives an algorithm that can be used to calculate the direct form coefficients from the lattice parameters.

Although the direct form and the lattice form of the least squares linear predictor are mathematically equivalent, the differences in their structures may give one form a clear advantage over the other in a specific use. A useful property of the lattice form is that the Mth order least squares lattice filter contains within its structure all lower order predictors. The pth order lattice filter can be obtained from the first p sections of an Mth order lattice structure. When a process is filtered with an Mth order lattice filter, the prediction errors and lattice parameters of all lower order lattice filters are available. This property is not shared by the direct realization of the least squares linear predictor. Separate direct forms are needed if it is desired to simultaneously perform linear prediction on a process with different orders of linear predictors. Simultaneous access to different order linear predictor results may be useful in the real-time analysis of AR processes with unknown order.

When compared with other adaptive linear predictors, the lattice form gives the Pre-Windowed Least Squares Lattice Filter computational advantages. Friedlander (1982a) divides adaptive processing methods into to categories: block processing and recursive techniques. The Pre-Windowed Least Squares Lattice Filter has a recursive parameter update algorithm. In block processing, incoming data are divided into blocks which are then used to estimate the prediction parameters. Block processing techniques update parameter estimation only once during a block period. In recursive techniques, predictor parameter estimates are updated with every new data. The recursive algorithm may be much more sensitive to changes in the input process that it needs to adapt to.

A particular feature of the Pre-Windowed Least Squares Lattice Filter that enhances its ability to adapt to changes in an input process is the exponential weighting factor, λ. In most application, the statistics of a process are slowly time-varying (Friedlander, 1982a). Because the linear predictor parameters depend on estimates of the statistics of the incoming process, it is necessary for the linear predictor to be able to track time variations in the statistics of incoming processes. λ determines the character of an exponential window that defines the set of past input data used to estimate the statistics of the input processes. The value of λ determines the shape and length of the exponential window. Older data samples have less weight than newer data samples in the estimation of process statistics. The exponential weighting factor aids the lattice filter in adapting to new trends in the input process by allowing it to forget past data values. Figure N3 illustrates the character of the exponential window for various values of λ.

Another important feature of the Pre-Windowed Least Squares Lattice Filter is the likelihood variable, $\gamma_{n,T}$ where n represents the order of the section the likelihood variable is being calculated for and T represents time. The likelihood variable enables the lattice filter to adapt quickly to sudden changes in the input process. The likelihood variable is closely related to the log-likelihood function of the lattice filter input process. Lee and Morf (1980) defined this relationship in the following way.

Assume that $\{y_t\}$ is a zero mean Gaussian process. The joint distribution for $\{y_T, \cdots y_{T-n}\}$ is

$$\rho(y_T, \cdots, y_{T-n}) = |2\pi R_n|^{-1/2} e^{\{-1/2[y_T, \cdots y_{T-n}]R_n^{-1}[y_T, \cdots y_{T-n}]'\}} \qquad \text{(N1)}$$

where

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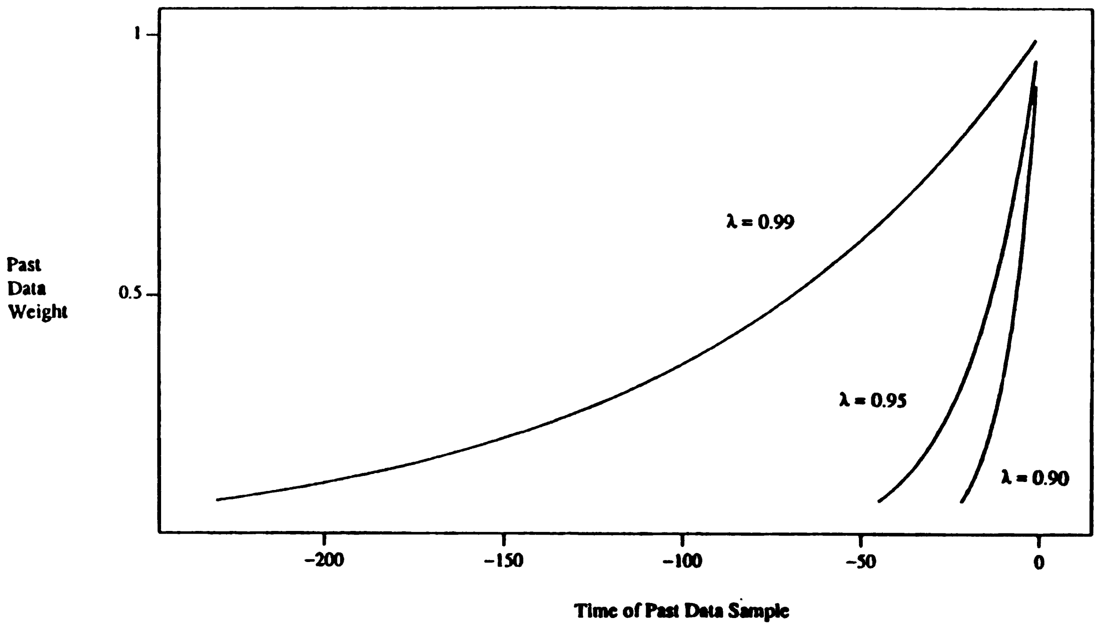

Figure N3. Character of the least squares lattice filter exponential window for various values of λ.

$$R_n = E[y_T, \cdots y_{T-n}]'[y_T, \cdots y_{T-n}]. \tag{N2}$$

The log-likelihood function associated with (N2) is proportional to

$$L = \ln|R_n| + [y_T, \cdots y_{T-n}]R_n^{-1}[y_T, \cdots y_{T-n}]'. \tag{N3}$$

The likelihood variable can be interpreted as the sample estimate of the second term in the log-likelihood expression of (N3) (Lee & Morf, 1980). The likelihood variable, $\gamma_{n,T}$ is a measure of the likelihood that successive data samples will come from the same Gaussian distribution (Lee & Morf, 1980). The likelihood variable is a good detection statistic of the "unexpectedness" of the most recent input data points (Friedlander, 1982a). The value of $\gamma_{n,T}$ ranges from 0 to 1. Lee and Morf reported that whenever non-Gaussian type components are present in the data, $\gamma_{n,T}$ tends to large values (close to 1). The factor $(1-\gamma_{n,T})$ is in the denominator of a gain used in the update recursions for certain lattice parameters (see Appendix E). As $\gamma_{n,T}$ approaches 1, the gain goes to ∞. The gain enables the lattice filter to quickly adapt to unexpected data (Lee & Morf, 1980).

The likelihood variable aided Lee and Morf (1980) in the detection of pitch pulses in speech processes. Their basic assumption was that the speech driving process consists of an approximately Gaussian part (for unvoiced speech) and a jump component (for voiced speech). Large linear prediction errors are good indications of the presence of a jump component or pitch pulse location in the excitation processes. Lee and Morf found that the locating pitch pulses from prediction errors could be done more accurately if the likelihood variable was used. Large changes in the likelihood variable corresponded to the occurrences of pitch pulses in the speech process. Lee and Morf showed how the derivative of the likelihood variable could be used as a mask in the extraction of the pitch pulses from the prediction error sequence. The likelihood variable was used to separate the Gaussian components from the highly non-Gaussian jump components of the speech driving processes. Byrne and Siegel (1985) directly applied the Lee and Morf technique to the problem of recovering heartbeat impulses from the microwave measurements.

A normalized version of the Pre-Windowed Least Squares Lattice Filter can be found in Friedlander (1982a). The normalization of the least squares lattice algorithm assures that the absolute values of the lattice filter's output and parameters are less than or equal to unity. One advantage of using the normalized least squares lattice filter is that it is easier to build a robust implementation of the filter when the range of the filter's parameters are known for every possible operating condition. Another advantage is that the normalized version of the lattice filter is less complex than the unnormalized version. After normalization, there are only three variables in the lattice filter parameter update equations. The unnormalized lattice filter has six variables (Friedlander, 1982a).

A possible disadvantage in using the normalized lattice filter is that the prediction errors are normalized. This may be a problem if one was trying to recover the exact excitation process that was used to synthesis the process under analysis. Friedlander (1982a) shows how the unnormalized lattice filter parameters and output can be calculated from the parameters of the normalized lattice filter.

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