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TIME-VARYING PARAMETRIC MODELING OF SPEECH*

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I. Introduction

Parametric analysis and modeling of signals using an autoregressive model with constant coefficients has found application in a variety of contexts including speech and seismic signal processing, spectral estimation, process control and others. In many cases, the signal to be modeled is time-varying. However, if the time variation is relatively slow, it is nevertheless reasonable to apply a constant model on a short-time basis, updating the coefficients as the analysis proceeds through the data [1], [2].

In this paper, we consider autoregressive signal modeling in which the coefficients are time-varying. In our method, each coefficient in the model is allowed to change in time by assuming it is a linear combination of some set of known time functions. Using the same least-squares error technique as used for modeling with constant coefficients (LPC, see Section II), the coefficients of the linear combinations of the time functions can be found by solving a set of linear equations. Therefore the determination of the model parameters for time-varying LPC is similar to that for traditional LPC, but there is a larger number of coefficients that must be obtained for a given order model.

There are many possible advantages of time-varying LPC. The system model may be more realistic since it allows for a continuously changing behavior of the signal. This should enable the model to have increased accuracy and sensitivity. In addition, the method may be more efficient since it will allow for the analysis over longer data windows. Therefore, even though time-varying LPC involves a larger number of coefficients than

traditional LPC, it will divide the signal into fewer segments. This could result in a possible reduction of the total number of parameters needed to accurately model a segment of data for time-varying LPC as compared with regular LPC.

An interesting problem in itself is the question of how exactly to measure and assess the performance of the time-varying LPC estimation method. One of the goals of this work has been to explore methods for understanding the time-varying models and for evaluating their performance.

II. Time-Varying Linear Prediction

For all-pole signal modeling, the signal $s(n)$ at time n is modeled as a linear combination of the past p samples and the input $u(n)$, i.e.,

$$s(n) = - \sum_{i=1}^p a_i s(n-i) + Gu(n). \quad (2.1)$$

The method of linear prediction (or linear predictive coding LPC) has been used to estimate the coefficients and the gain factor [1], [2]. For LPC, it is assumed that the signal is stationary over the time interval of interest and therefore the coefficients given in the model of Eq. 2.1 are constants. For speech, for example, this is a reasonable approximation over short intervals (10-30 msec).

For the method of time-varying linear prediction, the prediction coefficients are allowed to change with time, so that (2.1) becomes

$$s(n) = - \sum_{i=1}^p a_i(n) s(n-i) + Gu(n). \quad (2.2)$$

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With this model, the signal is not assumed to be stationary and therefore the time-varying nature of the coefficient $a_i(n)$ must be specified.

The actual time variation of $a_i(n)$ is generally not known. However, the coefficients can be approximated as a linear combination of some known functions of time, $u_k(n)$, so that

$$a_i(n) = \sum_{k=0}^q a_{ik} u_k(n). \quad (2.3)$$

With a model of this form the constant coefficients a_{ik} are to be estimated from the speech signal, where the subscript i is a reference to the time-varying coefficient $a_i(n)$, while the subscript k is a reference to the set of time functions $u_k(n)$. Without any loss of generality, it is assumed that $u_0(n) = 1$. Possible sets of functions that could be used include powers of time

$$u_k(n) = n^k \quad (2.4)$$

or trigonometric functions as in a Fourier series

$$\begin{aligned} u_k(n) &= \cos(k\omega n) & k \text{ even} \\ u_k(n) &= \sin(k\omega n) & k \text{ odd} \end{aligned} \quad (2.5)$$

where ω is a constant dependent upon the length of the speech data. Liporace [3] seems to have been the first to have formulated the problem as in Eq. 2.3. His analysis used the power series of the form of (2.4) for the set of functions.

From Eqs. 2.2 and 2.3, the predictor equation is given as

$$\hat{s}(n) = - \sum_{i=1}^p \left(\sum_{k=0}^q a_{ik} u_k(n) \right) s(n-i) \quad (2.6)$$

and the prediction error is

$$e(n) = s(n) - \hat{s}(n). \quad (2.7)$$

As in LPC, the criterion of optimality for the coefficients is the minimization of the total squared error

$$E = \sum_n e^2(n) = \sum_n \left(s(n) + \sum_{i=1}^p \sum_{k=0}^q a_{ik} u_k(n) s(n-i) \right)^2. \quad (2.8)$$

Minimizing the error with respect to each coefficient and defining

$$c_{k\ell}(i, j) = \sum_n u_k(n) u_\ell(n) s(n-i) s(n-j) \quad (2.9)$$

the coefficients are specified by the equation

$$\sum_{i=1}^p \sum_{k=0}^q a_{ik} c_{k\ell}(i, j) = -c_{0\ell}(0, j) \quad \begin{matrix} 1 \leq j \leq p \\ 0 \leq \ell \leq q. \end{matrix} \quad (2.10)$$

For the coefficient $c_{k\ell}(i, j)$, the subscripts k and ℓ refer to the set of time functions, while the variables inside the parentheses, i and j , refer to the signal samples. Since $u_0(n) = 1$, the time-varying LPC coefficients $c_{00}(i, j)$ are the same as the LPC coefficients.

The minimization of the total error results in a $p(q+1)$ set of equations that must be solved for the coefficients a_{ik} . The time-varying LPC equations reduce to the LPC equations for $q = 0$, that is, when $a_i(n)$ is a constant, $a_i(n) = a_{i0}$.

The limits of the sum over n can be chosen to correspond to the limits for the covariance and autocorrelation methods of LPC. For the covariance method, the sum over n goes from p to $N-1$, and (2.10) can be expressed in matrix form

$$\Phi \underline{a} = -\psi \quad (2.11)$$

$$\underline{a}_i^T = [a_{i1}, a_{i2}, a_{i3}, \dots, a_{ip}] \quad 0 \leq i \leq q \quad (2.12)$$

$$\underline{\psi}_i^T = [c_{0i}(0, 1), c_{0i}(0, 2), \dots, c_{0i}(0, p)] \quad 0 \leq i \leq q. \quad (2.13)$$

Also, Φ is a $(q+1) \times (q+1)$ block symmetric matrix with $(p \times p)$ symmetric blocks. The (i, j) element of the (k, ℓ) block of Φ is $c_{k\ell}(i, j)$.

Equation 2.10 can alternatively be expressed so that Φ is a $(p \times p)$ block symmetric matrix with $(q+1) \times (q+1)$ symmetric blocks (see [4]).

A similar, but not identical, set of equations, analogous to the autocorrelation method in the time-invariant case, can be formulated by windowing the data and minimizing the error over an infinite time interval. In this formulation, in order that the matrix Φ in Eq. 2.11 can be expressed as a block Toeplitz matrix, Eq. 2.3 is modified to

$$a_i(n) = \sum_{k=0}^q a_{ik} u_k(n-i) \quad 1 \leq i \leq p. \quad (2.14)$$

The limits of the error minimization for the time-varying covariance method have been chosen so that the squared error is summed only over those speech samples that can be predicted from the past p samples. However, the error for the time-varying autocorrelation method is minimized over the entire time interval (the same range that is used for the traditional LPC autocorrelation method). Therefore, the distortions of the LPC coefficients due to the discontinuities in the data at the ends of the interval evidenced in the time-invariant case apply also to the time-varying coefficients. This distortion in the coefficients

estimated by the autocorrelation method may or may not be significant depending on the data at the ends of the interval.

Windowing of the signal is a usual practice for the LPC autocorrelation method in order to reduce the distortion. However, even though windowing might reduce the end effects for the autocorrelation method, it also imposes an additional time variation upon the speech sample. This tends to cause two problems. The estimates of the coefficients by time-varying LPC will be adversely affected since the method, by its very formulation, is sensitive to any time variation of the system parameters such as that caused by the windowing of the signal. In addition, the window affects the relative weight of the errors throughout the interval. Since the windowed data at both ends of the interval will be smaller, there is more signal energy in the central data. Therefore the minimization of the error will result in coefficients that in general will reproduce the signal in the center of the interval better than at the ends.

Because of distortion in the estimates caused by the end effects when the data is not windowed and the possible adverse effects on the estimates when the data is windowed, the autocorrelation method seems to have more disadvantages than the covariance method. Since a window will have the same distortive effect for the covariance method, the use of a window does not seem beneficial.

Because the number of coefficients increases linearly with the number of terms in the series expansion ($q+1$), there is a significant increase in the amount of computation needed to determine the coefficients for time-varying LPC as compared with traditional LPC (where $q = 0$). However, techniques discussed in reference [4] can be used to make the coefficient determination efficient.

For example, most of the computational effort is involved with calculating the elements $c_{kl}(i, j)$ for Φ and Ψ using the summation of Eq. 2.9. But these elements can be computed very efficiently by taking advantage of the symmetry of Φ and because many elements can be easily calculated from previously computed elements without using Eq. 2.9. (It should be noted that the determination of the matrix elements is faster for the power series method than for the Fourier series method because no trigonometric functions need to be evaluated.)

Once the elements have been calculated, the set of equations must be solved to determine the coefficients. Liporace [3] has developed an efficient algorithm to solve the equations for the covariance method where Φ is a block symmetric matrix with symmetric blocks. The covariance method using the power series has the additional advantage that Φ can be expressed as a block Hankel matrix (where all the block matrices along the secondary diagonal, northeast to southwest, are equal) for which there is an efficient solution [5], [6]. For the autocorrelation method, Φ is a block Toeplitz matrix and there is an algorithm given in reference [7] for solving the equations. This method

is an extension of Levinson's recursion algorithm to the multichannel filtering problem.

III. Experimental Results for Synthetic Data

For the evaluation of time-varying linear prediction, the method used was to analyze synthetic data created by all-pole filters with known time-varying coefficients. The purpose of these test cases was to determine the general characteristics of time-varying LPC and to obtain some insight into methods for evaluating the performance of time-varying parameter identification techniques.

The first set of test cases was generated by all-pole filters excited by a periodic impulse train with each coefficient changing as a truncated power or Fourier series. Therefore for these cases, the form of the system model of the time-varying linear prediction analysis matched the actual system generating the data. The results of these cases indicated the differences between using the power or Fourier series for analysis, between using the covariance or autocorrelation method of error summation (as developed in Section II), and between windowing or not windowing the signal.

There were many conclusions to be drawn from these examples. The differences between using a power series or a Fourier series for the analysis seem to be insignificant. In general, a filter using one series can be represented almost exactly by a filter using the other series with either the same or a slightly larger number of terms in the series.

For example, the 6-2 power series filter* could be represented accurately as a 6-4 Fourier series filter, and a 6-2 Fourier series filter needed a 6-3 power series filter to represent it almost exactly.

The covariance method of summation gave better results than the autocorrelation method. Under some circumstances the differences between the two methods were minor, but this was not a general rule.

The use of a window had only a slight effect on the analysis results. Windowing did not significantly degrade the performance of the covariance methods and, in fact, the autocorrelation methods that used a window seemed to give more accurate results than the autocorrelation methods without a window.

These results can be explained, however, by the fact that the test cases were generated by a system whose form was the same as that of the analysis model. Therefore, these methods can estimate the coefficients of the series for the time-varying filter even with a window superimposed upon the signal because of the sample data in the central part of the interval.

However, actual signals are not generated by

* A 6-2 power series means 6 poles, ($p=6$), with each coefficient being a quadratic power series, ($q=2$).

the system model of time-varying LPC, and the use of a window will degrade the method's ability to track the time variation of the parameters accurately throughout the entire time interval. It does not seem that windowing is generally a good practice. In Section IV, the effect of windowing actual nonstationary speech on the analysis results will be shown.

All of this analysis indicates that the covariance method without windowing should be used. Since the results seem to be similar for either the power or Fourier series, the power series is preferred because of its computational advantage over the Fourier series method as discussed in Section II.

The second set of cases involved the response of the system to step changes in the center frequency of the poles. This study was carried out using a four-pole system. The center frequency of two poles changed discontinuously. The 6-3 covariance power method without windowing was used to analyze the data. Of interest is the trajectory of the center frequency of the first pole. The pole angle trajectories for different changes in the center frequencies are shown in Fig. 1. The trajectory of the poles for the time-varying linear prediction method is somewhat like the response of a

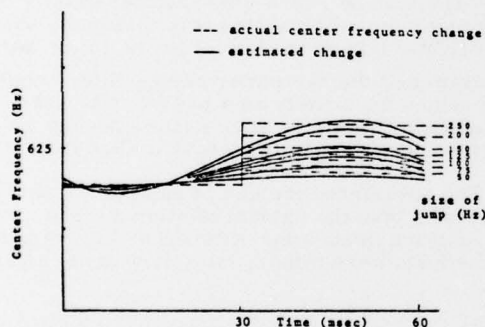


Fig. 1. Center frequency trajectories for 4-3 covariance power filter.

lowpass filter, but the response is anticipative since the entire interval is used to estimate the coefficients. In general, it was found that the system response is approximately homogeneous in that the pole angle trajectory for a given center frequency change is proportional to the size of the step change and is approximately additive in that the response to two different jumps in one interval is approximately the same as the sum of the responses to each jump taken separately in the same interval. Thus, the method can be thought of as acting like a linear lowpass filter in response to changes in the location of the poles. An estimate of the frequency response of the method's lowpass action was obtained from the computed step responses and is shown in Fig. 2 for the 4-3 and 4-5 covariance power filter. As we would expect, the 4-5 method has a broader "frequency response."

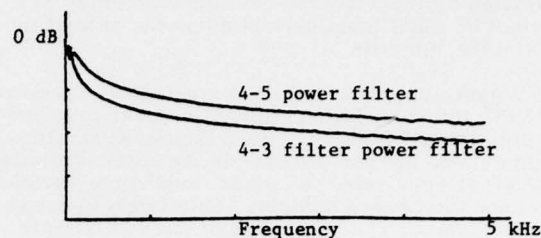


Fig. 2. Comparison of smoothed unit pulse frequency responses.

Therefore, it should be able to track changing center frequencies more accurately than the 4-3 method. LPC with constant coefficients tracked the step change of the center frequency slightly better than the 4-5 covariance power method did.

Test cases were also run to evaluate the ability to track slowly varying changes. Specifically, the first pole was varied linearly over the interval. It was found that time-varying linear prediction can handle linearly changing poles very well if the slope is small. For larger slopes the variation of the pole tends to be smeared over a larger interval. This supports the studies discussed earlier in this section in which we indicated that the method acted as a lowpass filter. Evidently, the higher slope changes are beyond the cutoff frequency of the method, yielding the same estimated pole trajectory as for an abrupt step change.

IV. Experimental Results for Time-Varying Analysis of Speech

In this section, we give an example of the application of time-varying LPC to a nonstationary speech waveform. Several different methods for evaluating the performance were used. The pole trajectories of time-varying LPC were compared with the poles of the time-invariant filters estimated by regular LPC. The log spectrum of each time-invariant LPC filter was also compared with the log spectrum of the time-varying filter evaluated at the time corresponding to the center of each of the analysis intervals used for regular LPC. As a measure of how well these spectra compare, a log spectral measure given by Gray and Markel [8] and Turner and Dickinson [9] was used. In addition, the impulse responses of both regular and time-varying LPC were compared with the original speech data. The time-varying model that was used was a 12-5 power series filter, and the analysis was performed on an interval of length 150 msec.

For regular LPC, a 12-pole filter was used and the length of each analysis interval was 20 msec. The center of the interval was shifted by 15 msec for each successive LPC analysis, resulting in some overlap of the data contained in each interval.

For the regular LPC analysis, the covariance

method was used, both with and without windowing the data. The results for both methods were so similar that only the covariance LPC method without windowing will be compared with the time-varying LPC method.

The pole trajectories for the covariance power series method both with and without windowing the data are shown in Fig. 3. This illustrates dramatically the effect of windowing, because there are

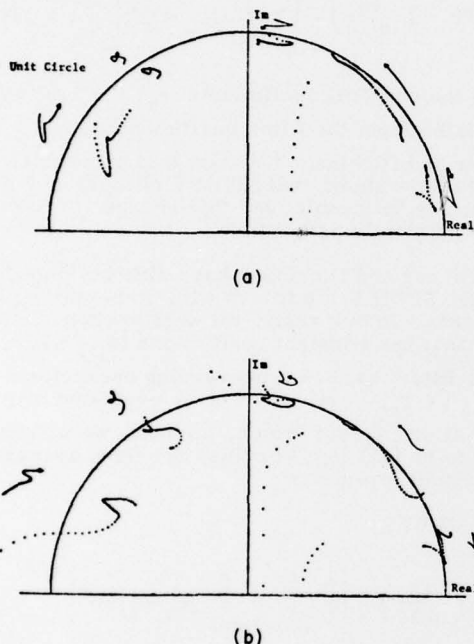


Fig. 3. Pole trajectories for 12-5 covariance power filter: (a) data not windowed, (b) data windowed.

poles of the filter for the windowed data that are outside the unit circle. For a time-invariant filter, this would mean that the filter was unstable. For a time-varying filter, this is not necessarily true. However, the few time-varying filters we have examined that have had some poles outside the unit circle have had impulse responses that usually remain bounded but excessively large. In general, the time-varying filter with poles outside the unit circle would seem to be of no practical value.

The pole trajectories for the 12-5 autocorrelation power series filter are shown in Fig. 4. Again, the autocorrelation filter for the windowed data has poles outside the unit circle. The results of the autocorrelation method (without windowing) agree favorably with that of the covariance method. The most significant differences occur at each end of the interval (as we would expect from our discussion in Section III).

This example shows that for any of the time-

varying methods discussed in this paper, there is no guarantee that the poles of the filter will remain inside the unit circle. This is a limitation of the time-varying method, but whether it is a serious problem in general practice is not known. Because windowing the data seems to increase the probability that the resulting filter will have poles outside the unit circle, it appears that the data should not be windowed. Since the covariance method seems better justified analytically than the autocorrelation method, the covariance power method

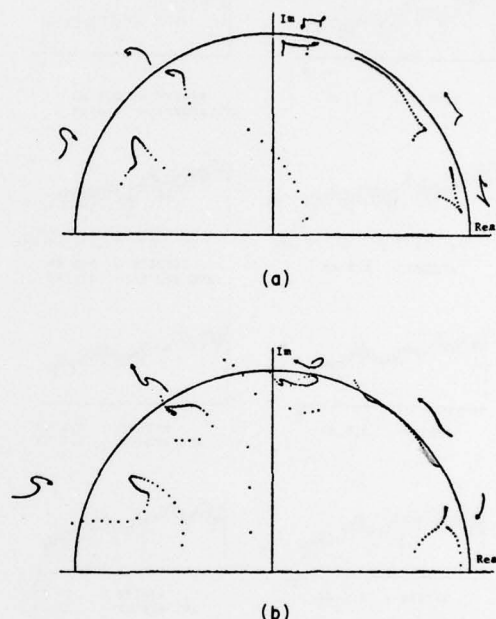


Fig. 4. Pole trajectories for 12-5 autocorrelation power filter: (a) data not windowed, (b) data windowed.

(without windowing) will be used for comparison with regular LPC.

For the covariance power method, it can be seen that there are only 5 sets of complex poles over much of the interval. The other two poles were generally real. This was also true occasionally for the time-invariant filters determined using regular LPC. For comparison purposes, only the five sets of poles that were always complex were compared with the time-invariant LPC poles.

The trajectories of the center frequencies for both methods agreed favorably. The main deviations between the time-varying method and regular LPC occurred in the first and second poles at the beginning of the time interval, where the "lowpass" nature of the time-varying LPC method is most evident. The time-varying method corresponded to "smoothed" values of the center frequency locations of regular LPC. The radius trajectories of

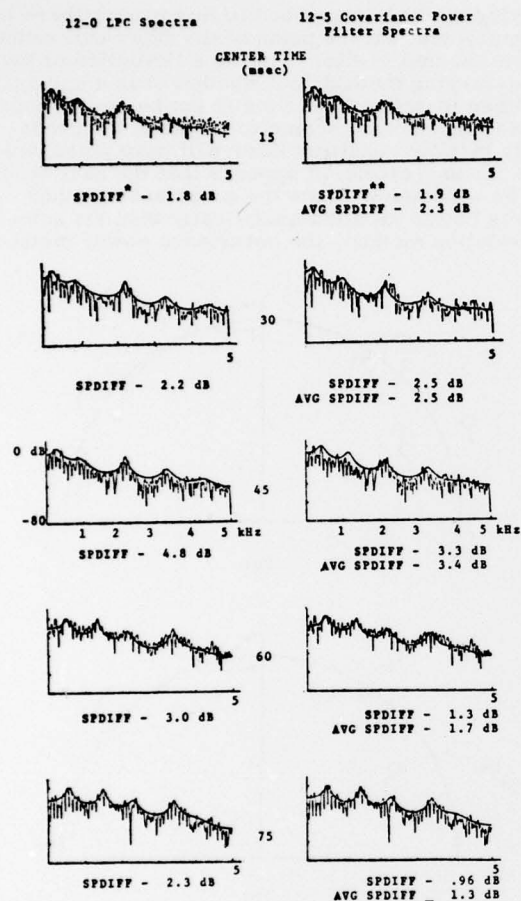


Fig. 5. Comparison of actual and filter spectra for preemphasized speech example.

* Difference between 12-0 (regular) LPC spectra for successive center times (i.e., between 15 and 30 msec).

** Difference (and average difference) between 12-0 and 12-5 filter spectra for same center time.

the poles agreed fairly well, except for the fifth pole. The center frequency trajectory of the fifth pole matched very well, while the radius trajectory did not. The radius trajectory deviations seem to be a result of the "lowpass" nature of the time-varying method.

Next we compared the log spectra of the all-pole time-invariant and time-varying filters with log spectra of the speech signal. The spectra were compared because LPC can be thought of as attempting to match the spectral envelope of speech with the spectrum of the all-pole filter. This is discussed in detail in [2]. For the time-varying case, the spectrum was defined at a time instant T as the frequency response of the filter with coefficients $a_i(k)$ to $i = 0, \dots, p$.

The spectra for the regular LPC and time-varying LPC filters for selected times are shown in Fig. 5. The spectra have been adjusted so that the largest value is 0 dB.

We used a log spectral measure to determine quantitatively the difference between the spectra for both LPC methods [8], [9]. This spectral measure SPDIFF is given by

$$\text{SPDIFF} = \left(\frac{10}{\ln 10} \right) \cdot \left[2 \sum_{k=1}^p (c_k - c_k^!)^2 \right]^{1/2} \quad (4.1)$$

Using the cepstral coefficients (c_k , $k = 1, p$) we calculated from the filter coefficients (a_k , $k = 1, p$).

Turner and Dickinson [7] state that perceptual studies have shown that SPDIFF changes of 2 dB are barely noticeable, but that changes of 3.5 dB are consistently perceptible.

Turner and Dickinson have also developed an average SPDIFF for filters with time-varying coefficients. In our study, we want to compare a filter that has constant coefficients (a_i , $i = 1, \dots, p$) with a filter that has time-varying coefficients ($a_i(n)$, $i = 1, \dots, p$), where n is evaluated over an interval of interest (which, for now, we will assume to be $[1, L]$). For this, the time-average spectral difference is

AVG SPDIFF

$$= \left(\frac{10}{\ln 10} \right) \cdot \left[\frac{1}{L} \sum_{n=1}^L 2 \sum_{k=1}^p (c_k - c_k^!(n))^2 \right]^{1/2} \quad (4.2)$$

where the cepstral coefficients are $c_k(n)$ using the coefficients ($a_i(n)$, $i = 1, \dots, p$). This is a measure of the average spectral difference between the time-invariant filter and the time-varying filter over the interval $[1, L]$.

The spectral difference, SPDIFF, between the regular LPC estimated filter and the time-varying LPC filter evaluated at the time corresponding to the center of the regular LPC analysis interval is given in the right-hand column of Fig. 5. The time average of the spectral difference, AVG SPDIFF, between the regular LPC filter and the time-varying filter for all the time steps n in the corresponding regular LPC analysis interval is also listed. As an indication of how quickly the speech spectrum is changing, the spectral difference between the regular LPC filters for successive analysis intervals is given in the left-hand column.

There are large spectral differences between the successive regular LPC time-invariant filters for the comparison times of 45 and 60, and 60 and 75 msec. These are the times in which the signal characteristics change significantly. The largest average spectral differences between the time-

varying LPC filter and the regular LPC time-invariant filters occur at the times of 30 and 45 msec. The values of the average spectral differences were 2.5 and 3.4, respectively, which would indicate that the differences between the two methods would be perceptible. After 60 msec, the average difference between the time-varying spectra and the time-invariant spectra were generally less than the difference between the time-invariant spectra for successive intervals, which would signify that the time-varying method is "tracking" the changing spectra very well.

The relatively large deviation of the time-varying spectrum from the actual speech spectrum for the times around 45 msec can be explained in part because of the "lowpass" action of the time-varying filter. The severity of the deviation is probably also due to the unequal energy distribution of the speech signal and of the impulse driving the system. The conclusion is that the time-varying filters should match the high energy areas of the nonstationary signal the best. In order to have a relatively good match over all the data in the interval, the energy of the signal or the driving impulses throughout the entire interval should be approximately equal. This is discussed further in [4].

References

1. J. I. Makhoul, "Linear Prediction: A Tutorial Review," Proc. IEEE, Vol. 32, April 1975, pp. 561-582.
2. J. D. Markel and A. H. Gray, Jr., Linear Prediction of Speech, Springer-Verlag, New York, 1977.
3. L. A. Liporace, "Linear Estimation of Nonstationary Signals," J. Acoust. Soc. Am., Vol. 58, No. 6, pp. 1268-1295, December 1975.
4. M. G. Hall, "Time-Varying Linear Predictive Coding of Speech Signals," S.M. Thesis, Dept. of Electrical Engineering and Computer Science, Mass. Inst. of Tech., Cambridge, Mass., August 1977.
5. J. Rissoner, "Algorithms for Triangular Decompositions of Block Hankel and Toeplitz Matrices with Applications to Factoring Positive Matrix Polynomials," Mathematics of Computation, Vol. 27, 1973, pp. 147-154.
6. J. J. Cornyn, Jr., "Direct Methods for Solving Systems of Linear Equations Involving Toeplitz or Hankel Matrices," Rept. AD/A-002 931, prepared for U.S. Office of Naval Research, October 1974; also S.M. Thesis, University of Maryland, College Park, Md.
7. R. A. Wiggins and E. A. Robinson, "Recursive Solutions to the Multichannel Filtering Problem," J. Geophys. Res., Vol. 70, 1965, pp. 1885-1891.
8. A. H. Gray, Jr., and J. D. Markel, "Distance Measures for Speech Processing," IEEE Trans. on Acoust., Speech and Sig. Proc., Vol. 24, No. 5, October 1976, pp. 380-391.
9. J. Turner and B. Dickinson, "Linear Prediction Applied to Time-Varying All-Pole Signals," in Proc. 1977 IEEE Int. Conf. on Acoust., Speech and Sig. Proc., pp. 750-753.

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20. Abstract

linear predictive coding, but there is a larger number of coefficients that must be obtained for a given order model.

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