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Lossless compression of seismic data

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Abstract

Data compression techniques are commonly used to achieve a low bit rate in the digital representation of signals for efficient processing, transmission, and storage. In this paper, a new technique for lossless compression of seismic data is introduced. The technique consists of two stages. The first stage is a modified linear prediction with discrete coefficients that is developed based on the assumption that the seismic data can be modeled as a sum of finite number of complex sinusoids in additive noise. In the second stage, the parameters and residual sequence of seismic data model are bi-level coded. Experimental results performed using real seismic data are presented to demonstrate the effectiveness of the new modeling approach.

1. Introduction

The focus of this research work is on lossless seismic data compression. The importance of such a subject stems from the fact that there are many locations on the earth that contain stations for measuring earthquakes and explosions made by the humans. The amount of data received by these stations is more than a gigabyte of data per day (10^9 byte), assuming that each sample is represented as a 4-byte signed integer value. Since the trend is toward increasing the sampling frequency of continuously recorded data, the estimated amount of data will triple; hence, compression is needed.

Lossless compression is not a new problem in the general context of computing. A variety of utilities such as WinZip are available and widely used to compress text and program files

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for storage or transmission over the internet. These programs are designed to be very effective for text data. For example, a postscript version of this section occupied 99.5 KBytes of storage, while the WinZip version occupied only 11.4 KBytes of storage; a compression ratio (CR) of $\frac{99.5}{11.4} = 8.73$. On the other hand, a seismic data file consisting of 32-bit samples used in our tests, occupied 2.197 MBytes of storage before compression and 0.628 MBytes after compression with WinZip. In this case, the CR was only 3.49. Therefore, the need for algorithms specifically designed for seismic data compression is obvious.

Although, lossless compression of seismic data has not received a great deal of attention so far, a number of algorithms have been developed [1–9]. These algorithms have two stages in common. The first is a decorrelation stage which exploits redundancy between neighboring samples in a data sequence, and the second stage is an entropy encoder which takes advantage of the decreased variance of the data.

In Section 2, a new modeling approach for seismic data compression is proposed. This approach is based on the assumption that seismic data can be modeled as a sum of finite number of complex sinusoids with random phases in additives noise. Experimental results demonstrating the effectiveness of our new approach are presented in Section 3. Concluding remarks are drawn in Section 4.

2. Seismic data modeling

Most algorithms model seismic data using the method of linear prediction. This method has become the predominant technique for representing seismic data for low bit rate transmission or storage. The importance of this method lies both in its ability to provide extremely accurate estimates of seismic data parameters, and in its relative speed of computation. The basic idea behind linear predictive modeling is that a seismic data sample $x(n)$ can be approximated as a linear combination of past seismic data samples $x(n\text{-}1)$, $x(n\text{-}2)$, … etc. In this section, we introduce new predictors based on the assumption that seismic data $\{x(n)\}$ can be modeled as a sum of L complex sinusoids with random phases in additive noise; that is,

$$x(n) = \sum_{i=1}^{L} A_i \mathrm{e}^{\left\{\mathrm{j}(\omega_i n + \varphi_i)\right\}} + v(n), \tag{1}$$

where $\mathrm{j} = \sqrt{-1}$, A_i is the amplitude of the ith sinusoids, $\{\phi_i\}$ are random phases that are uniformly distributed and independent of each other, and $v(n)$ is zero-mean white noise of variance σ^2, that is assumed to be independent of the phases $\{\phi_i\}$. Such a model has been successfully applied in a number of applications including sonar signal processing and speech signal processing [10]. Let us define the following two (q+1)-length vectors

$$\mathbf{X}_n = [x(n)x(n-1)\ldots x(n-q)]^{\mathrm{H}},$$
$$\mathbf{S}_\omega = [1\mathrm{e}^{\mathrm{j}\omega}\,\mathrm{e}^{2\mathrm{j}\omega}\ldots\mathrm{e}^{\mathrm{j}q\omega}]^T,$$

where q is an integer and 'H' denotes Hermittian transpose. Therefore, the autocorrelation matrix $\mathbf{R} = E\left\{\mathbf{X}_n\mathbf{X}_n^H\right\}$ of the signal $x(n)$ can be written in the following compact form

$$\mathbf{R} = \mathbf{SPS}^{\mathrm{H}} + \sigma^2\mathbf{I}, \tag{2}$$

where $\mathbf{I}$ is the (q+1) × (q+1) identity matrix, $\mathbf{P}$ and $\mathbf{S}$ are the $L \times L$ diagonal power matrix and the $(q+1) \times L$ sinusoidal matrix, that are defined as follows:

$$\mathbf{P} = diag\{P_1, P_2, \ldots, P_L\},$$

$$\mathbf{S} = [S_{\omega 1}, S_{\omega 2}, \ldots, S_{\omega L}]$$

where P_i is the power of the ith sinusoid. The linear predictive model parameters, denoted by $\{a_k\}_{k=1}^{8}$, are determined by minimizing the mean-squared prediction error (MSE) ζ. If the prediction error is expressed as

$$e(n) = x(n) - \sum_{k=1}^{q} a_k x(n-k), \tag{3}$$

it can be shown that

$$\begin{aligned} \zeta &= E\left\{ |e(n)|^2 \right\} \\ &= \sum_{i=1}^{L} P_i \left| A\left(e^{j\omega_i}\right) \right|^2 + \sigma^2 a^H a, \end{aligned} \tag{4}$$

where $\mathbf{a} = [1 - a_1 - a_2 \ldots a_q]^H$ and $A\left(e^{j\omega}\right) = S_\omega^H \mathbf{a}$. The minimum of ξ is obtained when $A(e^{j\omega})$ exhibits very sharp spectral null at the sinusoidal frequency. Infinite resolution can, in principle, be achieved if we can find a polynomial $A(z)$ that has zeros on the unit circle at the desired frequency; namely,

$$z_i = e^{jw}, \quad i = 1, 2, \ldots, L. \tag{5}$$

To satisfy this condition, the degree q of the polynomial $A(z)$ must necessarily be $q \geqslant L$; then, the remaining q-L zeros of $A(z)$ could be arbitrary. Noting that $A\left(e^{j\omega}\right) = \mathbf{S}_\omega^H \mathbf{a}$, therefore we have

$$\mathbf{S}^H a = \begin{bmatrix} A\left(e^{j\omega_1}\right) \\ A\left(e^{j\omega_2}\right) \\ \vdots \\ A\left(e^{j\omega_L}\right) \end{bmatrix} = 0. \tag{6}$$

Multiplying both sides of (2) by $\mathbf{a}$ and making use of (6), we obtain

$$\begin{aligned} \mathbf{Ra} &= \mathbf{SPS}^H a + \sigma^2 \mathbf{a} \\ &= \sigma^2 \mathbf{a}. \end{aligned} \tag{7}$$

Eq. (7) implies that σ^2 must be an eigenvalue of $\mathbf{R}$ with $\mathbf{a}$ is the corresponding eigenvector. Note that $\mathbf{R}$, as given in (2), is the sum of two matrices: the autocorrelation matrix of the sinusoidal component $\mathbf{R}_s = \mathbf{SPS}^H$ and the autocorrelation matrix of the noise component $\mathbf{R}_n = \sigma^2\mathbf{I}$. The eigendecomposition of matrix $\mathbf{R}$ possesses a special structure. Let $\{\lambda_i\}$ be the eigenvalues of $\mathbf{R}$ that are arranged in decreasing order,

$$\lambda_1 \geqslant \lambda_2 \geqslant \ldots \geqslant \lambda_{q+1}.$$

Since $\mathbf{R} = \mathbf{R}_s + \mathbf{R}_n$, then $\lambda_i = \lambda_i^s + \sigma^2$ where $\left\{\lambda_i^s\right\}$ re the eigenvalues of matrix $\mathbf{R}_s$. However, because $\mathbf{R}_s$ has rank L, it follows that $\mathbf{R}_s$ has only L nonzero eigenvalues. Therefore, the first L eigenvalues of $\mathbf{R}$ are greater than σ^2 and the remaining eigenvalues equal to σ^2. Thus, the eigenvalues and eigenvectors of $\mathbf{R}$ may be divided into two groups. The first group, consisting of the L eigenvectors that have eigenvalues greater than σ^2, are referred to as signal eigenvectors and span an L-dimensional subspace called the signal subspace. The second group, consisting of those eigenvectors that have eigenvalues equal to σ^2, are referred to as the noise eigenvectors and span an (M–L)-dimensional subspace called the noise subspace. Since $\mathbf{R}$ is Hermittian, the eigenvectors form an orthonormal set. Therefore, the signal and noise subspaces are orthogonal. That is to say, for any vector $\mathbf{u}$ in the signal subspace and any vector $\mathbf{g}$ in the noise subspace, $\mathbf{u}^{\mathrm{H}}\mathbf{g} = 0$.

2.1. Eigenpredictors

The development presented above indicates that the desired polynomial $A(z)$ can be found by solving the eigenvalue problem (7) and selecting the eigenvector corresponding to the minimum eigenvalue. This step which requires the extraction of the noise subspace from the observation subspace is computationally intense. In what follows, we assume that $L = 2$. By so doing, we simplify the problem and make it possible to determine explicit mathematical expression for $A(z)$, with zeros on the unit circle, without the need to the standard eigendecomposition of matrix $\mathbf{R}$. Effectiveness of the models based on such assumption will be thoroughly investigated in Section 3.

The simplest form of eigenpredictors that can model a sinusoidal signal with two complex exponentials is the three-coefficient causal filter that has two zeros at $z = \mathrm{e}^{\pm \mathrm{j}w}$, and is given by

$$\begin{aligned} A(z) &= z^{-1}(z - \mathrm{e}^{-\mathrm{j}\omega 0})(1 - z^{-1}\mathrm{e}^{\mathrm{j}\omega 0}) \\ &= 1 - 2z - 1 \cos \omega_0 + z^{-2}. \end{aligned} \tag{8}$$

The effect of the parameter ω_o on the predictor frequency response is shown in Fig. 1. The z-transform of the four-coefficient predictor can be obtained by introducing a third zero at $z = 1$, as shown below

$$\begin{aligned} A(z) &= (1 - z^{-1})(1 - 2z^{-1} \cos \omega_0 + z^{-2}), \\ A(z) &= 1 - (1 + 2 \cos \omega_0)z^{-1} + (1 + 2 \cos \omega_0)z^{-2} - z^{-3}. \end{aligned} \tag{9}$$

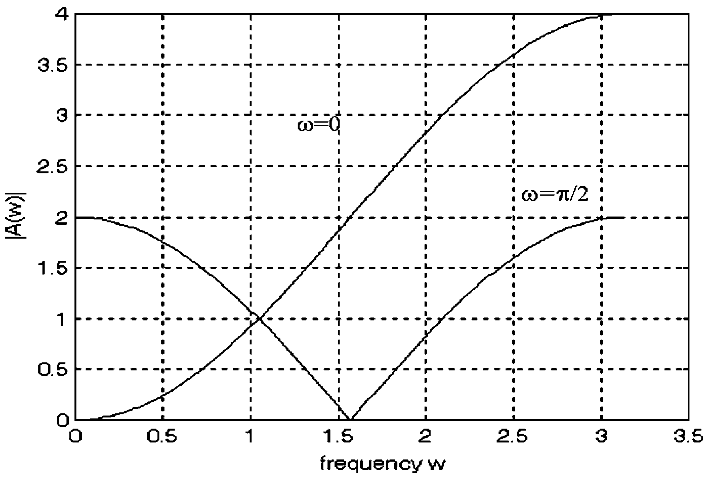

Fig. 1. Predictor frequency response.

Similarly, we can derive a five-coefficient predictor by convolving the impulse response of the three-coefficient predictor with that of a predictor whose frequency response has two zeros at $z = 1$. Because convolution maps to multiplication in the z-domain, it follows that

$$\begin{aligned} A(z) &= (1 - z^{-1})^2(1 - 2z^{-1} \cos \omega_0 + 2z^{-2}) \\ &= 1 - (2 + 2 \cos \omega_0)z^{-1} + (2 + 4 \cos \omega_0)z^{-2} - (2 + 2 \cos \omega_0)z^{-3} + z^{-4}. \end{aligned} \tag{10}$$

An advantage of the development presented here is that it includes the work of [7] as a special case. Specifically, by setting $\omega = 0$ in Equations (8)–(10), we obtain

$$A(z) = \begin{cases} 1 - 2z^{-1} + z^{-2}, & q = 2, \\ 1 - 3z^{-1} + 3z^{-2} - z^{-3}, & q = 3, \\ 1 - 4z^{-1} + 6z^{-2} - 4^{-3} + z^{-4}, & q = 4. \end{cases} \tag{11}$$

These predictors have been developed based on the differentiation approach. This approach is implemented by taking the difference between adjacent signal samples. For low-frequency signals, the differences between consecutive samples tend to be quite small when compared to the original signal. For high-frequency signals, the reverse is true; however, seismic signals are generally dominated by low-frequency components. In any event, examining Eq. (11), we observe that the first predictor is, in fact, a second-order differentiator, while the second and third predictors are third-order and fourth-order differentiators, respectively.

2.2. Implementation issues

As in the case of most lossless seismic coders, the proposed compression algorithm divides the input seismic data into independent frames, typically of length 1000 samples. The input frames are then applied to four simple FIR predictors as shown in Fig. 2. The outputs of these predictors are given by

$$\begin{aligned} r_0(n) &= x(n), \\ r_1(n) &= x(n) - x(n-1) \\ r_2(n) &= x(n) - Q[2 \cos \omega_o x(n-1) - x(n-2)] \end{aligned}$$

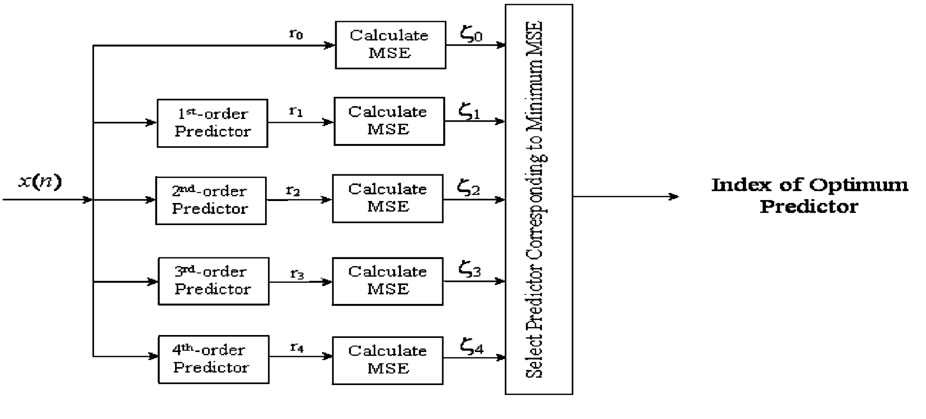

Fig. 2. Selection of optimum predictor.

$$r_3(n) = x(n) - Q[(1 + 2\cos\omega_o)(x(n-1) - x(n-2)) - x(n-3)]$$
$$r_4(n) = x(n) - Q[(2 + 2\cos\omega_o)(x(n-1) + x(n-3)) - (2 + 4\cos\omega_o)x(n-2) - x(n-4)], \quad (12)$$

where $Q[.]$ denotes rounding to the nearest integer. The predictor with index i that minimizes the following MSE:

$$\zeta_i = E\{r_{ii}^2(n)\}, \quad i = 0, 1, \ldots, 4 \quad (13)$$

is selected to represent the current frame under consideration. To compute ζ_i based on the definition above, we have to average across all the sample functions of the random process $r_i(n)$. In practice, however, ζ_i is often computed by the substitution of time averages for ensemble averages, e.g.,

$$\zeta_i = \frac{1}{N-q-1} \sum_{n=q+1}^{N-1} r_i^2(n), \quad (14)$$

where N is the size of the input data frame and q is the number of predictor coefficients. Note that the last three predictors given in Eqs. (12) have only one unknown parameter, namely, ω_o. This parameter is determined by minimizing the mean-squared error ζ_2. The main motivation behind the use of ζ_2 for determining ω_o is due to the simplicity of the model generating the residual sequence $r_2(n)$.

3. Performance evaluation

3.1. Seismic database

The standard seismic database presented in Table 1 used for the evaluation portion of this study was supplied by Dr. Hard Bolton of the Albuquerque Seismological Laboratory a division of the USGS (United State Geological Survey). It consists of eight waveforms recorded at three stations: ANM at Albuquerque, New Mexico, RAR at Raratonga in the Cook Island Chain in the South Pacific, and KIP at Kipapa in the Hawaiian Islands. Two of the waveforms are long-period (1 Hz sampling rate), two are broadband (20 Hz sampling rate), and two are high frequency (100 Hz sampling rate). In addition, there are two waveforms containing significant seismic events recorded at ANM, one a broadband

Table 1
Seismic data classifications

File no.	File name	Number of samples	Sample rate sample/s	Maximum value	Minimum value
1	Anmbhz89	67 000	20	478743	−495441
2	Anmbhz92	72 000	20	123	−1368
3	Anmehz92	14 000	100	7735	−6639
4	Anmlhz92	86 000	1	329	−5956
5	Kipehz13	62 000	100	177	−215
6	Kipehz20	61 000	100	893	−728
7	Rarbhz92	72 000	20	12317	−13793
8	Rarlhz92	86 000	1	55810	−55072

recording of the 1989 Lorna Prieta earthquake and one a high-frequency recording of a small local event.

The database includes waveforms from seismically noisy as well as quiet sites. Taken as a whole it represents an average or typical mix of the data recorded on the worldwide seismic network. Since the seismic database is typical of continuous physical waveforms data, compression results obtained using the database should be of value to everyone who requires lossless compression of waveform data, in computer storage and archiving as well as in real-time satellite and other telemetry situations. Table 2 shows the estimated first-order entropy H_1 for each seismic data file. For signals such as seismic data where there is considerable sample-to-sample correlation, the actual entropy will be significantly lower than H_1. However, these entropy estimates, which are all less than 32 bits, suggest that some degree of lossless compression should be possible in all cases.

3.2. Histograms of residual sequence

Figs. 3 and 4 show the histograms of the residual sequences of files 4 and 8, respectively, computed at the output of the second-order predictor with λ_{op}. and $\lambda = 1$. The optimum value of λ is computed as follows: input data is first partitioned into fixed-length sequences or data frames, each having N integer samples. The parameter N has been given the value 1000. For each frame λ_{opt} is computed by minimizing ζ_2. The second-order predictor with λ_{opt} is then used to convert each data frame to a prediction error or residual sequence.

Based on the results depicted, we observe that the residual sequences have amplitude distributions that are approximately Gaussian with zero mean. A second important observation is that using λ_{opt} has noticeable effect on files 4 and 8. Specifically, the dynamic range of residual errors of these files when computed using λ_{opt} is much smaller than the dynamic range of residual errors of the same files when computed using $\lambda = 1$.

Table 2
Entropy H_1, of seismic database

File 1	File 2	File 3	File 4	File 5	File 6	File 7	File 8
7.04	3.78	6.7	11.39	3.78	5.57	6.84	15.38

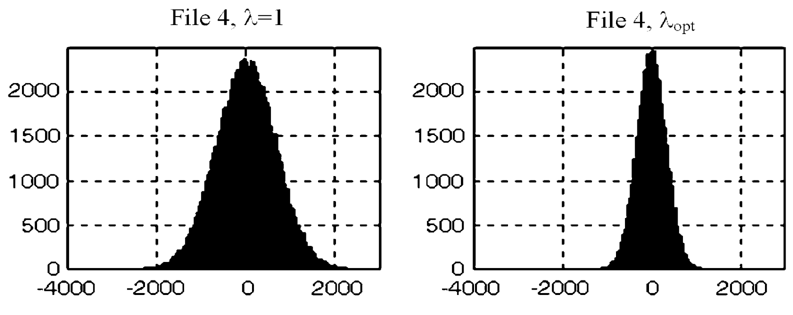

Fig. 3. Histogram of file 4, λ_{opt} and λ_1.

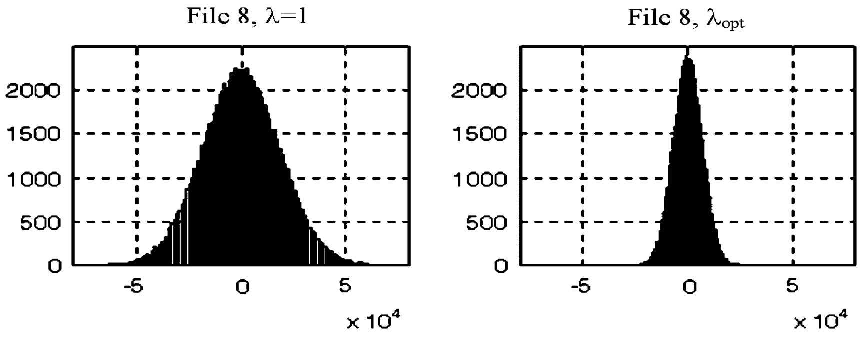

Fig. 4. Histogram of file 8, λ_{opt} and λ_1.

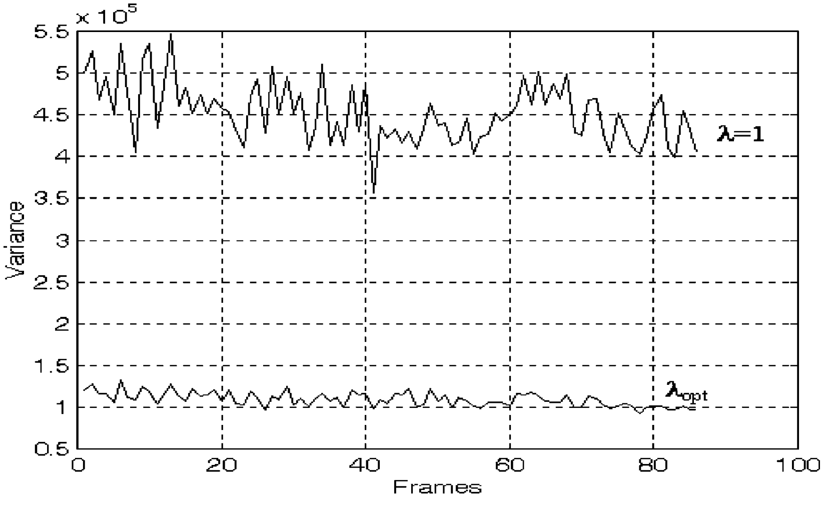

Fig. 5. Variance of file 4 for $\lambda = 1$ and λ_{opt} versus frame number.

The above observation can be further confirmed by plotting the variance value of residual sequence for each frame against the frame number. Figs. 5 and 6 show the results for both $\lambda = 1$, and $\lambda_{opt.}$. Note that the variance of file 4 processed with λ_{opt} is about 24.15% of the variance of residual sequence computed with $\lambda = 1$. It is however worth noting that processing the data with λ_{opt} has an advantage in that the variance of resulting residual sequences is always smaller than or equal to that of residual sequences computed using $\lambda = 1$.

3.3. Selection of optimal predictor

The compression algorithm presented in this work makes use of five predictors that are defined in Eq. (12). For each frame, the five prediction residuals $r_0(n)$, $r_1(n)$, $r_2(n)$, $r_3(n)$, and $r_4(n)$ are computed at every sample in the frame and the square of their values is averaged over the complete frame. The predictor that has residual with the smallest mean-squared value is then selected to represent that frame. Table 3 shows the number of times each

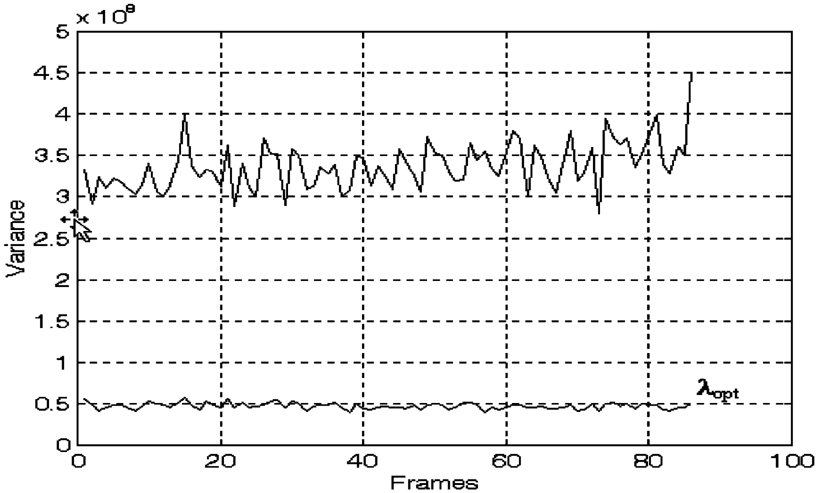

Fig. 6. Variance of file 8 for $\lambda = 1$ and λ_{opt} versus frame number.

Table 3
Number of times each predictor was chosen when λ_{opt} is obtained using $r_2(n)$

File	Filter									
	λ_{opt}					$\lambda = 1$				
	1	2	3	4	5	1	2	3	4	5
File 1	0	0	25	34	8	0	0	8	49	10
File 2	0	0	72	0	0	0	0	72	0	0
File 3	0	0	14	0	0	0	11	3	0	0
File 4	0	0	86	0	0	0	86	0	0	0
File 5	0	61	1	0	0		61	1	0	0
File 6	0	0	57	4	0	0	0	13	48	0
File 7	0	0	70	2	0	0	0	49	23	0
File 8	0	0	86	0	0	86	0	0	0	0

predictor was chosen to represent a given frame of the eight data files. In this computation, λ_{opt} is determined by minimizing the mean-squared value of residue sequence at the output of second-order predictor. The optimum value of λ is then used in the computation of residual sequences of the third and fourth-order predictors. In Table 4, λ_{opt} is computed for each predictor by minimizing the mean-squared value of residual sequence of that predictor.

As seen from the tables, there are minor changes in the number of times each predictor is selected to represent a given frame as far as the case of λ_{opt} is concerned. Therefore, the gain that might be achieved by optimizing λ for each predictor is of small value that makes this optimization process is impractical due to the attendant of extra modeling complication and effort.

Table 4
Number of times each predictor was chosen when λ_{opt} is obtained for each filter

File	Filter									
	λ_{opt}					$\lambda = 1$				
	1	2	3	4	5	1	2	3	4	5
File 1	0	0	25	35	7	0	0	8	49	10
File 2	0	0	70	0	2	0	0	72	0	0
File 3	0	0	14	0	0	0	11	3	0	0
File 4	0	0	86	0	0	0	86	0	0	0
File 5	0	61	1	0	0		61	1	0	0
File 6	0	0	52	9	0	0	0	13	48	0
File 7	0	0	61	2	9	0	0	49	23	0
File 8	0	0	86	0	0	86	0	0	0	0

A second observation that can been drawn from the tables is as follows. The sequence $r_0(n)$ has never been selected with the optimized linear predictors, while it has been chosen 86 times in the case of $\lambda = 1$. Since this number is equal to the total number of frames of file 8 and that $r_0(n)$ is nothing but the input data as defined in Eq. (11), therefore it can be concluded that linear predictors with $\lambda = 1$ are incapable of modeling data file 8.

A third observation that can be drawn from Tables 3 and 4 is that there is no strong preference for any of the predictors with $\lambda = 1$; i.e., there is an advantage in varying the predictor from frame to frame. This is, however, not the case with the optimized predictors. Examining the results presented, we find that $r_2(n)$ is the most dominant residual sequence that has been selected. Therefore, $r_2(n)$ computed with λ_{opt} can serve as an approximation to a given frame in all cases when the computational complexity is of a major concern.

3.4. Compression ratio (CR)

The fact that λ_{opt} has a wide dynamic range makes it possible to achieve better performance in terms of CR if optimized predictors are being used. Figs. 7 and 8 show the CR versus the frame number for data files 4 and 8 using $\lambda = 1$ (corresponding to the results of [7]) and λ_{opt} (corresponding to the proposed method in this work). In our computation we have set $N = 1000$.

Note that because of the nonstationary nature of seismic data, the CR for $\lambda = 1$ is changing from frame to frame. Table 5 shows the effect of frame size on the CR, where we observe that for most cases there is slight improvement in performance when frame length is increased. It is relevant at this point to refer the reader to Table 3 in [9] which presents results for other seven different compressions methods using the same seismic database described in Table 5 of this section. Compared to the results of Table 5, some of these algorithms have better compression performance at the expense of increased computational complexity.

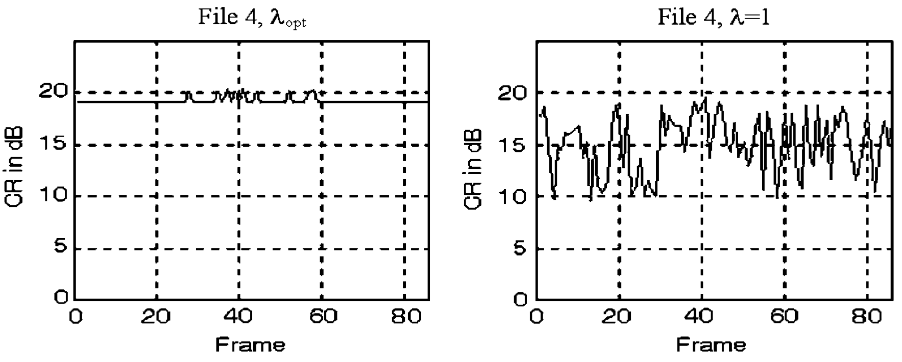

Fig. 7. Compression ratio versus frame number for file 4.

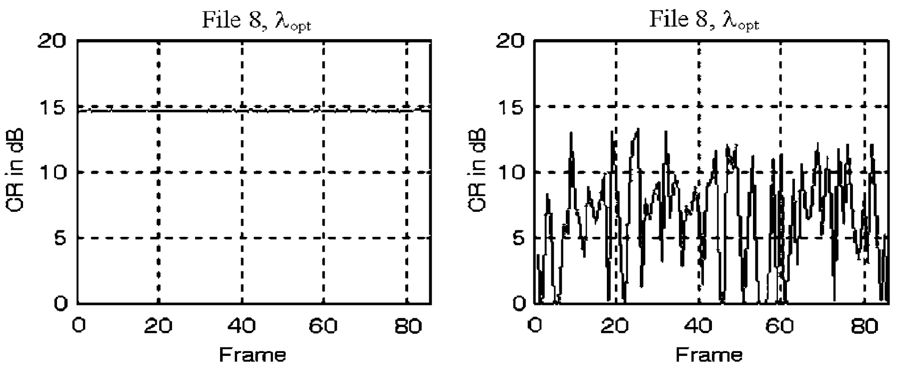

Fig. 8. Compression ratio versus frame number for file 8.

Table 5
CR Versus frame length

File	Frame size			
	128	256	512	1024
File 1	4.9335	4.7868	5.1182	5.2549
File 2	7.4368	7.437	7.437	7.4675
File 3	4.6677	4.6303	4.7236	5.0843
File 4	2.615	2.6198	2.6199	2.6496
File 5	7.4034	7.4429	7.4478	7.5185
File 6	5.6136	5.6382	5.6217	5.7286
File 7	4.4425	4.4521	4.4527	4.4696
File 8	2.0805	2.0805	2.0812	2.1064

4. Conclusions

In this paper, we have developed a new compression algorithm using the basic principles of framing, prediction, and entropy coding. This algorithm consists of five simple eigenpredictors.

Eigenpredictors introduced in this work have an advantage in that they include the linear predictors of [7] as a special case. Furthermore, each eigenpredictor has integer coefficients and only one parameter to optimize λ. Experimental results show that by optimizing λ, variance of residue sequence can be reduced and CR can be improved. In addition to that we have found the second-order eigenpredictor with optimized λ is the most dominant predictor that has been selected to produce the residual sequence. Therefore, this low-order eigenpredictor with λ_{opt} can serve as a model to a wide range of seismic data when the computation complexity is of a major concern.

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