Seismic Data Compression using GenLOT: towards "optimality"?

Laurent C. Duval, laurent.duval@ifp.fr,
Van Bui-Tran, van.bui-tran@ifp.fr
Institut Français du Pétrole, 1 et 4 av. de Bois-Préau
92852 Rueil-Malmaison Cedex, France
Truong Q. Nguyen, nguyent@engc.bu.edu
Boston University, ECE Department, 8 St. Mary's street
Boston MA 02215, USA
Trac D. Tran, ttran@ece.jhu.edu
The Johns Hopkins University, ECE Department, 3400 N. Charles Street
Baltimore, MD 21218-2686, USA

Abstract

GenLOT coding has been shown an effective technique for seismic data compression, especially when compared to block-based algorithms (such as JPEG), or to wavelets. The transforms remove statistical redundancy and permit efficient compression, when used with advanced encoding techniques, such as the Embedded Zerotree Coding framework. In this work we derive a model for seismic data based on auto-regressive processes. This model is used to design GenLOT filter banks optimized for seismic data, using objective optimization criteria.

1 Introduction

Seismic data compression is desirable in geophysics for both storage and transmission stages. Wavelet coding methods [DEP98] are effective for compressing seismic data. They have generated interesting developments, including software and hardware implementation for a real-time field test trial in the North Sea in 1995 [VED96]. Newer methods, involving local cosine bases [Mey99], non-unitary filter banks [RWRA99] or generalized lapped orthogonal transforms (GenLOTs) have been developed to overcome some of the wavelet shortcomings by incorporating additional features in the transform. Recent works in image processing have shown than GenLOT with proper design outperforms wavelet compression for natural images [TN99]. Some of the authors have shown in a previous work [DN99] that GenLOT with basic optimization also outperforms state-of-the-art biorthogonal wavelet coders for seismic data. In this work, we focus on the problem of filter bank optimization using various properties of seismic data. Seismic data used in this paper was acquired by the French Institute for Petroleum (IFP) in 1996 in the Forêt d'Orléans, France. A seismic stack section, shown in Fig. 1, is modeled by autoregressive processes up to order 4 and is compared to the results using the conventional model with 0.95 intersample correlation (for natural images). The experiment shows that data-based optimization is desirable in order to obtain the best from the progressive GenLOT seismic coder described in [DON99].

2 Motivations of data-based optimization

Most of the transform-based image coders, such as the standard JPEG coder or Said and Pearlman's SPIHT [SP96] compress the rows and columns separately, using for instance block DCT or biorthogonal wavelets, respectively. More precisely, the transform stage is applied in a "separate fashion" to the rows and columns, considered as 1-D $x(i)$ signals. The encoding process is often 2-D in nature, in order to encompass more efficiently the 2-D structure of the image. These include the JPEG zig-zag order or the Embedded Zerotree Coding introduced by J.-M. Shapiro [Sha93] and the extended method by Said and Pearlman [SP96]. They have better performance comparing to the method that uses pure 1-D raster scan coding of the transformed coefficients.

It is often desirable to evaluate the compression performance of a transform on a set of data using *a priori* objective measures. The purpose is two-fold:

- first, to avoid or drastically reduce extensive testings of many available transforms by selecting only *a priori* good transforms;
- secondly, by tailoring the transforms to the statistical properties of the data set.

One of the most commonly used objective criterion for filter bank (i.e., transform) is the coding gain. It can be used as a measure of energy compaction improvement over a basic pulse code modulation (PCM), when using a transform or a subband compression scheme instead of PCM [JN84]. The following sections demonstrate the use of coding gain along with stopband attenuation and DC leakage optimization for seismic data compression. The filter banks obtained through optimization in this work are used within the seismic coder proposed by the authors [DON99] at the latest meeting of the Society of Exploration Geophysicists.

3 Signal modeling

Let x be a realization of an 1-D real-valued autoregressive process of order n, abbreviated as $\mathrm{AR}(n)$. We assume that x has unit variance $\sigma_x = 1$ and prediction coefficients $b_1, b_2, b_3, \ldots$ Let r_x be the normalized auto-covariance function (Acf) of x. The right hand side of the Acf also follows a noiseless AR (n) model, with the same prediction coefficients $b_1, b_2, b_3, \ldots$ For $i \geq n$, we have:

$$r_x(i) = b_1 r_x(i-1) + b_2 r_x(i-2) + \ldots + b_n r_x(i-n). \quad (1)$$

In the simple case of an AR(1) process, ρ_1 is the first normalized coefficient, corresponding to $r_x(1)$. The Acf then is given by:

$$r_x(i) = \rho_1^{|i|}. \quad (2)$$

SNAR(n) denotes the above Symmetric Noiseless Autoregressive process with order n. In image compression applications, the Acf of 1-D signal is classically modeled as SNAR(1), with intersample correlation $\rho_1 = 0.95$ [Mal92, SN96].

4 Seismic signal modeling

In this section, we discuss the modelling aspect of seismic data using autoregressive process. If we try to model seismic signals with an autoregressive process, classical linear progressive coding (LPC) often leads to non stable regression coefficients. One reason could be that seismic signals are often considered as non stationarity. Nevertheless, if we consider the autocovariance function only, Røsten *et al.* [RMRP99] have already shown that SNAR(1) or 2 give good results in filter bank optimization.

In the scope of this work, we use SNAR models up order 4, at which the validity of the model becomes doubtful, as seen in Table 1. Let $\rho_0, \ldots, \rho_3$ be the first four autocovariance coefficients $r_x(0), \ldots, r_x(3)$. The correlation coefficients are then given by:

$$\rho_0 = 1 \quad (3)$$

$$\rho_1 = \frac{(1-b_4)(b_1+b_3b_4)+b_2(b_3+b_1b_4)}{(1-b_4)(1-b_2-b_2b_4-b_4^2)-(b_1+b_3)(b_3+b_1b_4)} \quad (4)$$

$$\rho_2 = \frac{b_2+(b_1+b_3)\rho_1}{1-b_4} \quad (5)$$

$$\rho_3 = b_3+(b_2+b_4)\rho_1+b_1\rho_2 \quad (6)$$

$$r_x(i) = b_1 r_x(i-1) + b_2 r_x(i-2) + \ldots + b_4 r_x(i-4), \quad i \geq 4. \quad (7)$$

The coefficients b_i are obtained directly by calculations on r_x, and not on the signal x to avoid coefficient unstability. The coefficients ρ_is are derived from Eq. 7 and from Acf's symmetric property:

$$r_x(i) = r_x(-i) \quad (8)$$

Setting $b_1 = b_2 = b_3 = 0$, and then $b_2 = b_3 = 0$ yields the two SNAR models given in Jayant and Noll [JN84]:

$$r_x(|i|) = \rho_1^{|i|}. \quad (9)$$

and

$$
\begin{aligned}
r_x(0) &= 1 && (10)\\
r_x(1) &= \frac{b_1}{1-b_2} && (11)\\
r_x(i) &= b_1 r_x(i-1) + b_2 r_x(i-2). && (12)
\end{aligned}
$$

respectively.

Each horizontal or vertical line of the stack section displayed in figures 1 gives different coefficients, and they are averaged to obtain an average model of the horizontal and vertical signals. The model parameters are summarized in Table 1.

Direction	Order	b_1	b_2	b_3	b_4
Vertical	1	0.8523 (0.024)			
	2	1.2500 (0.050)	-0.4670 (0.057)		
	3	1.1593 (0.039)	-0.2259 (0.054)	-0.1923 (0.038)	
	4	1.1499 (0.041)	-0.2329 (0.045)	-0.1457 (0.028)	-0.0404 (0.048)
Horizontal	1	0.9393 (0.037)			
	2	0.9344 (0.095)	0.0068 (0.077)		
	3	0.9325 (0.030)	-0.0225 (0.094)	0.0558 (0.037)	

Table 1: Averaged prediction coefficients for models with orders 1 to 4

In the later case (horizontal direction, order 3), since the second averaged coefficient, -0.0225, is much smaller than its standard deviation, we thus do not expect this model to be very accurate.

5 Filter bank (Transform) design

Several criteria are used for transform optimization: for instance, *coding gain* (CG) optimization usually correlates with higher SNRs (objective measure). Other objective measures include *stopband attenuation* or *DC leakage* (DC). Though not essential, they often improve the visual quality of the reconstructed data.

Coding gain Let x, σ_x and σ_{x_i} be the input signal, its variance and the variance of the ith subband, respectively, and $\|f_i\|$ be the L_2-norm of the ith filter. Under appropriate assumptions, such as optimal bit rate allocation (cf. [RAH95] for a comprehensive survey), the coding gain can be formulated as

$$C_C = 10 \log_{10} \frac{\sigma_x^2}{\prod_{i=0}^{M-1} \sigma_{x_i}^2 \|f_i\|^2}. \qquad (13)$$

Stopband attenuation Here, the stopband criterion is chosen to be the contribution of all the filters' energy outside of F_i passband, denoted as Ω_i:

$$C_S = \sum_{i=0}^{M-1} \int_{\Omega_i} |F_i(e^{j\omega})|^2 d\omega. \qquad (14)$$

DC leakage The DC leakage measures the part of the DC energy that overlaps out of lowpass subband. It can be defined as:

$$C_D = \sum_{i=0}^{M-1} \sum_{j=0}^{L-1} f_i(j). \tag{15}$$

The above objective measures can be weighted in the overall cost function C_o:

$$C_o = k_C C_C + k_S C_S + k_d C_D. \tag{16}$$

We refer to T. Tran's article [TN99] for more detailed issues on filter bank optimization, and comparison to wavelet coders for natural images.

6 Optimization results

In this chapter, a 8-channel GenLOT with length 16 is used in the simulation. The following design steps yield filter bank with good objective measure:

1. first, start from a lattice with optimal stopband attenuation (S),
2. then, maximize the coding gain (C),
3. end with DC leakage minimization (D).

Results are given in signal to noise ratio (SNR) vs. compression ratio in tables 2-4. The letter S in the top row denotes results obtained from filter banks with only stopband attenuation measure whereas SC n denotes results obtained from filter banks with stopband attenuation measure followed by coding gain maximization with SNAR order n, and SCD denotes the results obtained from filter banks with the complete optimization procedure. It is worth noting that, if the S and C steps often lead to (local) maximum, the SCD filter banks often result from uncompleted optimization (no minimum reached after 20.000 iterations), denoted by the star symbol $*$. This explains why we only display the minimum and the maximum SNRs at this step. In tables 2-3, we first display the optimization results in one direction only. The transform for the other direction is chosen to be the DCT. Table 4 shows the GenLOT gain over block 8×8 DCT and Malvar's LOT with 8 channels and 16 taps.

Ratio	S	SC0	SC1	SC2	SC3	SC4	Min SCD*	Max SCD*
20	40.31	42.75	42.76	43.03	43.08	43.08	43.90	44.05
50	31.30	32.12	32.12	32.42	32.46	32.47	33.73	33.76
80	28.60	29.20	29.20	29.23	29.49	29.46	30.75	30.77

Table 2: GenLOT optimization in the vertical "time" direction vs. DCT.

From Tab. 4, we can see that, when the design procedure reaches a local maximum, (*e.g.* when we perform only stopband attenuation followed by coding gain

Ratio	S	SC0	SC1	SC2	SC3	Min SCD*	Max SCD*
20	40.17	41.32	41.31	41.33	41.34	42.00	42.02
50	30.42	31.66	31.67	31.67	31.70	32.87	32.89
80	27.41	28.82	28.83	28.83	28.88	30.19	30.20

Table 3: GenLOT optimization in the horizontal "space" direction vs. DCT.

Ratio	DCT	LOT	Min. SCD*	Max. SCD*
20	41.66	44.09	44.21	44.38
50	32.52	33.93	34.04	34.08
80	29.81	30.99	31.06	31.09

Table 4: Comparison between DCT, LOT and pseudo-optimal GenLOTs

optimization) the resulting SNR increases nearly monotonously with the model order. And even if a local maximum is not reached, at high bit rates or low distortion, partial optimization may yield results up to 3.5 dB better compared to basic stopband optimization, or 1.30 dB to 0.95 intersample correlation modeling. This is particularly interesting for raw seismic data sets, where the DCT can be used in the horizontal direction because of the poor correlation in the space direction, cf. [DON99]. Even in the stack case, with a little more horizontal correlation, a simple first order models might be sufficient in general, while vertical direction may require models with higher order.

7 Conclusion

Data based GenLOT optimization is desirable for seismic data, since simple SNAR models are sufficiently reliable at low prediction orders. Furthermore, even non complete optimization procedures lead to good objective results. Convergence problems nevertheless need to be addressed, in order to obtain more optimal filters.

8 Acknowledgments

The authors would like to thank Steffen Trautmann, who provided us with the Matlab™optimization routines, which have been used in the article [TN95]. Other results on GenLOT optimization can be found at the Waveweb site, `http://saigon.ece.wisc.edu/~waveweb/`.

Figure 1: Seismic stack section from Forêt d'Orléans.

References

[DEP98] P. L. Donoho, R. A. Ergas, and R. S. Polzer. Improved data management for interpretation systems using compression. In *Proc. 60th EAGE Conference*, 1998.

[DN99] L. C. Duval and T. Q. Nguyen. Seismic data compression: a comparative study between GenLOT and wavelet compression. In M. Unser, A. Aldroubi, and A. F. Laine, editors, *Wavelet Applications in Signal and Image Processing VII*. Proc. SPIE 3813, Jul. 1999.

[DON99] L. C. Duval, J. Oksman, and T. Q. Nguyen. A new class of filter banks for seismic data compression. In *Proc. 69th Annual SEG Int. Meeting*, Oct. 1999.

[JN84] N. S. Jayant and P. Noll. *Digital Coding of Waveforms*. Prentice-Hall, Inc., Englewood Cliffs, NJ, 1st edition, 1984.

[Mal92] H. Malvar. *Signal Processing with Lapped Transforms*. Artech House, 1992.

[Mey99] F. G. Meyer. Fast compression of seismic data with local trigonometric bases. In M. Unser, A. Aldroubi, and A. F. Laine, editors, *Wavelet Applications in Signal and Image Processing VII*. Proc. SPIE 3813, Jul. 1999.

[RAH95] T. A. Ramstad, S. O. Aase, and J. H. Husøy. *Subbands compression of images: principles and examples*. Elsevier, 1995.

[RMRP99] T. Røsten, V. A. Marthinussen, T. A. Ramstad, and A. Perkis. Filter bank optimization for high-dimensional compression of pre-stack seismic data. In *Proc. Int. Conf. on Acoustics, Speech, and Signal*, March 1999.

[RWRA99] T. Røsten, P. Waldemar, T. A. Ramstad, and L. Amundsen. Subband coding of 2-D seismic data, part I: Theory and optimization. *Submitted to Geophysics*, 1999.

[Sha93] J. M. Shapiro. Embedded image coding using zerotrees of wavelet coefficients. *IEEE Trans. on Signal Processing*, 41:3445–3462, Dec. 1993.

[SN96] G. Strang and T. Nguyen. *Wavelets and Filter Banks*. Wellesley-Cambridge Press, Wellesley, MA, 1996.

[SP96] A. Said and W. A. Pearlman. A new fast/efficient image codec based on Set Partitioning in Hierarchical Trees. *IEEE Trans. on CAS for Video Technology*, 6:243–250, Jun. 1996.

[TN95] S. Trautmann and T. Q. Nguyen. GenLOT – design and application for transform-based image coding. In *Proc. 29th Asilomar Conference on Signals, Systems and Computers*, pages 41–45, 1995.

[TN99] T. D. Tran and T. Q. Nguyen. A progressive transmission image coder using linear phase uniform filter banks as block transforms. *IEEE Trans. on Image Processing*, 8:1493–1507, Nov. 1999.

[VED96] J. D. Villasenor, R. A. Ergas, and P. L. Donoho. Seismic data compression using high-dimensional wavelet transforms. In *Proc. 6th Data Compression Conference*, pages 396–405. IEEE computer society press, Apr. 1996.

Figure 2: Auto-covariance for one vertical signal.

Figure 3: Auto-covariance models for one horizontal signal.