Residual multiple attenuation using AVA modeling

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In the present approach, the AVA modeling problem consists of determining the three parameters A, B and C of equation (**??**) by solving the following data fitting problem:

$$\mathbf{L}\mathbf{m} = \mathbf{d}, \tag{1}$$

where $\mathbf{L}$ in matrix form is

$$\begin{bmatrix} \mathbf{1}_1 & \mathbf{S}_1 & \mathbf{T}_1 \\ \mathbf{1}_2 & \mathbf{S}_2 & \mathbf{T}_2 \\ \mathbf{1}_3 & \mathbf{S}_3 & \mathbf{T}_3 \\ \vdots & \vdots & \vdots \\ \mathbf{1}_{n_1} & \mathbf{S}_{n_1} & \mathbf{T}_{n_1} \end{bmatrix} \tag{2}$$

which has dimension $n_1 n_2 \times 3n_1$, $\mathbf{m}$ is the model-parameter vector ($3n_1$ elements), and $\mathbf{d}$ is the data vector ($n_1 n_2$ elements), where n_1 and n_2 are the number of samples in depth (or time) and the number of traces in the ADCIG, respectively. $\mathbf{1}_j$, $\mathbf{S}_j$ and $\mathbf{T}_j$ are $n_2 \times n_1$ matrices consisting of 1, $(\sin^2\theta_i)$ and $(\tan^2\theta_i)$ along their j-th column entries, respectively. i stands for the reflection-angle indexes.

$$\mathbf{1}'s = \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 & 0 & 0 \\ 0 & 1 & 0 & \cdots & 0 & 0 & 0 \\ 0 & 0 & 1 & \cdots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & 1 & 0 & 0 \\ 0 & 0 & 0 & \cdots & 0 & 1 & 0 \\ 0 & 0 & 0 & \cdots & 0 & 0 & 1 \end{bmatrix} \tag{3}$$

Generally, in ADCIGs, residual multiples are more persistent at near angles, because of insufficient moveout difference between them and the flattened primaries. Additionally, at the farthest angles, stretch occurs. To avoid these imperfections in the input data, the fitting goal is to minimize the residual,

$$\mathbf{0} \approx \mathbf{M}(\mathbf{L}\mathbf{m} - \mathbf{d}), \tag{4}$$

where $\mathbf{M}$ is a selector operator which applies the appropriate internal and external mutes.

If unrealistic variations of the AVA parameters with depth are an issue, the following regularization goal can be introduced:

$$\mathbf{0} \approx \epsilon\mathbf{D}\mathbf{m}, \tag{5}$$

where $\mathbf{D}$ is the derivative operator along depth and ϵ is the regularization parameter. As usual, care must be taken when choosing ϵ not to destroy any recoverable residual moveout information and not to spread simulated primaries to angles at which they originally do not occur.

To accelerate the solution, the problem can be solved with preconditioning (Claerbout and Fomel, 2001), using the transformation $\mathbf{m} = \mathbf{Cp}$, where $\mathbf{C} = D^{-1}$ and $\mathbf{p}$ is the preconditioned variable. Finally, the fitting goals reduce to

$$\begin{aligned} \mathbf{0} &\approx \mathbf{M}(\mathbf{LCp} - \mathbf{d}) \\ \mathbf{0} &\approx \epsilon\mathbf{p}. \end{aligned} \tag{6}$$

The final model is obtained with $\mathbf{m} = \mathbf{Cp}$. I use conjugate-gradients to solve the inverse problem.

After the determination of the three AVA parameters for every depth step, primaries are simulated by computing the reflection coefficient for all reflection angles using equation (**??**). Of course, the method relies on the flatness of the reflectors in the CIG to correctly extract the 3 parameters of the AVA curve.

To get the residual-multiple-attenuated data, the adaptive subtraction must be applied in two steps. The first one aims to obtain an estimate of the residual multiples. This is done by subtracting the adjusted version of the simulated primaries from the original data. Amplitude and phase adjustments are achieved by the convolution of the simulated primaries with a prediction-error Wiener filter.

As the estimated residual multiples may contain some primary information (mainly at small reflection angles), I use the strategy proposed by Guitton et al. (2001), the so-called 'subtraction method,' in which two different prediction-error filters (PEFs), which model primaries and multiples, are computed. Their method allows regularization, to decrease the crosstalk between multiples and primaries. The corresponding fitting goals are

$$\begin{aligned} \mathbf{0} &\approx \mathbf{m}_n \\ \mathbf{0} &\approx \epsilon\mathbf{m}_s \\ \text{subjected to} \leftrightarrow \mathbf{d} &= \mathbf{S}^{-1}\mathbf{m}_s + \mathbf{N}^{-1}\mathbf{m}_n \end{aligned}$$

after preconditioning, with $\mathbf{s} = \mathbf{S^{-1}m_s}$ and $\mathbf{n} = \mathbf{N^{-1}m_n}$. In the preconditioning equations, $\mathbf{s}$ represents the primaries, $\mathbf{n}$ the multiples; $\mathbf{N}^{-1}$ and $\mathbf{S}^{-1}$ represent deconvolution with PEFs for multiples and primaries, respectively; $\mathbf{m_n}$ is the multiple model content and $\mathbf{m_s}$ is the primary model content. Finally, the estimated primaries are obtained by $\hat{\mathbf{s}} = \mathbf{d} - \mathbf{N}^{-1}\mathbf{m_n}$. All PEFs are computed with conjugate-gradients.

CONCLUSIONS

I present a simple and fast method, based on AVA modeling, to obtain simulated primaries for estimating residual multiples, in such a way that they can be further attenuated. The method relies on the flatness of the input CIGs. I apply the method to a GOM 2D data set which has strong residual multiples with complex geometries. The method proves its efficiency in attenuating residual multiples, yielding cleaner images than the original ones. In principle, any residual noise which does not obey the flatness criteria in a CIG can be attenuated by the method.

REFERENCES

Claerbout, J. and S. Fomel, 2001, Image estimation by example: Geophysical soundings image reconstruction: `http://sepwww.stanford.edu/sep/prof/gee2.06.pdf`.

Guitton, A., M. Brown, J. Rickett, and R. Clapp, 2001, A pattern-based technique for ground-roll and multiple attenuation: SEP–**108**, 249–274.