A STOCHASTIC MODEL FOR SEISMOGRAM ANALYSIS

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Abstract

The blocky or box-car appearance of well logs suggests that, stochastically, they can be modeled as Markov chains. Minimizing the number of parameters necessary to describe the Markov chain results in a stochastic model which we call a general telegraph wave. Such a parsimonious description, while neglecting small scale features of well logs, preserves the blocky property in simulated well logs. The general telegraph wave describes not only well logs but also acoustic impedance and reflectivity. The corresponding time series are highly non-Gaussian, a property that can be advantageously used when developing algorithms for seismogram deconvolution and inversion.

An algorithm that iteratively removes the source waveform present in a suite of seismograms is developed and tested on real data. Assuming a non-Gaussian reflectivity model, both the color and phase effects of the source waveform are removable from the seismogram. The main ingredient in the algorithm is a zero-memory (instantaneous) non-linear estimator of reflection coefficient amplitude. Forcing a filtered version of the seismogram to resemble these estimates is accomplished iteratively.

Finally, an algorithm that converts a deconvolution into acoustic impedance is proposed. Here, the memory in the estimator, a consequence of modeling impedance as a dependent process, plays a key role in confining the resulting impedance function to a corridor of minimum-maximum values. A feature of the algorithm is the ability to merge additional information, besides the deconvolution, into the computation of impedance. For instance, low frequency impedance information, as provided by mean square velocity curves, can be easily incorporated into the algorithm.

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Introduction

Geophysicists are commonly presented with the problem of having to estimate acoustic impedance from seismograms. The estimation is usually considered in two stages. First, the source waveform and all multiples are removed from the seismogram and the resulting deconvolved seismogram is then transformed into acoustic impedance. We call the latter process seismogram inversion. The problem of deconvolving multiples from seismograms is not addressed in this thesis; here the term deconvolution should always be preceded by the adjective "source waveform." For those datasets in which multiples are significant and must be removed, the theory presented here will offer no help. In areas where multiples can be neglected, however, the mathematical models for source waveform deconvolution and seismogram inversion proposed in this thesis may prove useful. We use a statistical estimation theoretic approach to construct the models.

The statistical approach to model building was elegantly summarized by Box and Jenkins (1970, p.7):

> "...The idea of using a mathematical model to describe the behavior of a physical phenomenon is well established. In particular, it is sometimes possible to derive a model based on physical laws, which enables us to calculate the value of some time-dependent quantity nearly exactly at any instant of time... Probably no phenomenon is totally deterministic, however, because unknown factors can occur. In many problems we have to consider a time dependent phenomenon for which it is not possible to write a deterministic model that allows exact calculation of the future behavior of the phenomenon. Nevertheless, it may be possible to derive a model that can be used to calculate the probability of a future value lying between two specified limits. Such a model is called a probability model or a stochastic model..."

The main component in each mathematical model is the prescription of a stochastic model describing reflectivity, in the case of source waveform deconvolution, and impedance, in the case of seismogram inversion. Actually such a prescription is implicit in any model of deconvolution or seismogram inversion. Some recent non-Gaussian models have had significant success. Wiggins (1977) developed a deconvolution technique that minimized, heuristically, the entropy in a deconvolution. Since Gaussian models maximize the entropy, his use of a non-Gaussian model is evident. Another approach, pioneered by Claerbout and Muir (1973) and subsequently refined by Taylor, Banks and McCoy (1979), uses the L-1 vs. the L-2 norm to minimize deconvolution residuals. Both sets of authors point out the robustness property of the L-1 norm. In addition, Scargle (1977) has shown that the L-1 norm is capable of determining phase information when reflectivity is non-Gaussianly distributed, while the L-2 norm isn't. We also use non-Gaussian models here. The significant difference between our approach and those above is that we use the stochastic model explicitly in the problem formulation.

A model that has been used by some earth scientists to describe the randomness observed in stratigraphic sequences is the Markov chain. Krumbein and Dacey (1969) noted that simulations using the Markov chain approach yielded synthetic sections similar to those seen in nature, especially in cyclical deposits. Schwarzacher (1972) used a two state Markov chain to simulate periods of deposition and non-deposition in a random sedimentation model that he proposed. The time spent in a transition from one state to the other controlled the amount of deposition. Such a model is called a semi-Markov or Markov renewal model. A summary of probabilistic methods as applied to geology is given by Merriam (1972) and the reader is referred to it for a complete list of references.

The Markov model is not the sole descriptor of acoustic impedance. The problem of formulating a stochastic model so that acoustic impedance can be estimated from seismograms has a dual in speech processing. There, sound generated in the vocal system (source waveform) is spectrally shaped by the transmission characteristics of the vocal tract (acoustic impedance). Given a speech signal, speech analysis is concerned with estimating the parameters of a model describing the vocal tract. Commonly, the process of speech production is modelled as a time-varying linear system (vocal tract) excited by a periodic pulse (sound generation). A summary of techniques available for estimating the parameters of the model is given by Schafer and Markel (1979). These techniques offer alternatives to the Markov model that we adopt.

The first chapter develops a stochastic model for impedance. A general telegraph wave, a particular type of Markov chain, is used. The stochastic model describing reflectivity follows from the model for impedance. One reason for choosing impedance as the fundamental process is that geologically it's easier to describe the occurrence of rock units than of reflection coefficients. Various properties of the model, e.g. reversibility, Bussgangness, etc., are developed in Chapter I. The remaining chapters utilize the stochastic model in formulating solutions to a few inverse problems in reflection seismology.

The problem of removing the source waveform from a seismogram has traditionally been attempted using predictive deconvolution. The phase of the waveform, however, is indeterminable using this technique and to assure a unique solution, minimum phase is usually assumed. But the concept that the earth's reflection coefficients are non-Gaussianly distributed allows both the color and phase of the waveform to be determined. Chapter II develops an iterative deconvolution technique to do this. The main ingredient in this algorithm is a zero memory non-linear estimator of reflection coefficient amplitude. The zero memory property follows from assuming that reflectivity is independent. This is inconsistent with the Markov model proposed in Chapter I; however, results indicate that such an approximation is valid in the present application.

The final chapter shows how the Markov model of impedance can be used to deglitch well logs and, more importantly, to convert a deconvolution into an impedance. Given the deconvolution, a non-linear estimator of impedance is used to perform the inversion. Here the estimator has memory, whereas in Chapter II it was memoryless. When integrating the deconvolution, the memory plays a critical role in confining impedance to a corridor of minimum-maximum values.

In summary, a non-Gaussian, dependent model of impedance (and therefore reflectivity) has been proposed. This model can be used effectively to develop new algorithms to solve old problems.

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