Seismic Facies Identification and Classification Using Simple Statistics
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Abstract
The identification and mapping of rock facies is important to reliable reservoir characterization. Traditionally, facies identification and mapping is based on inspection of core data and/or well-log signatures, a procedure that has subjective aspects as it is relies on samples from only a very small portion of the reservoir. Such identification is also difficult to perform at the onset of the exploration stage due to lack of sufficient well data. This paper demonstrates a simple, practical approach to identify and classify facies from seismic amplitude data using basic statistical concepts.

Within a geologic facies, measured properties (in this case acoustic impedance or AI) are assumed to differ mainly as a result of random additive events and are modeled by a normal distribution, as justified by the central limit theorem. The facies are identified by estimating the combination of facies volume fractions and distribution parameters (means and standard deviations of the facies probability density function), that best fit the population distribution of AI. A simple form of Bayes theorem is then used to compute the probability of occurrence of each of the facies at the measured locations. This generates a volume of facies probabilities corresponding to the seismic volume. Such a volume can be used to perform facies-specific petrophysical analysis or be a starting point to generate multiple realizations of petrophysical properties. The approach is easy and transparent to use with no significant computational requirements even on large data sets.

We describe an application of the procedure to a synthetic reference data set and a Gulf of Mexico AI data set. Mapped probabilities of the individual facies show the spatial continuity and geologic character of the underlying depositional environment. Property values within the mapped regions are substantially less variable than the original data over the entire region. The within-facies semivariograms exhibit much less spatial correlation than across all facies. Since the facies are mapped over an exhaustive data volume, this approach considerably reduces the need for the geostatistical construction of property distributions within them as long as a high correlation exists between the seismic attribute and petrophysical properties.

Introduction
One of the first steps involved in building a reservoir model is to identify the facies present and to map their spatial distribution. This is typically done using the geological information available from early well logs and cores and the interpretation of seismic amplitude data. Knowledge of the facies present in the area of study results in better application of correlations that are used to generate spatial maps of petrophysical properties. However, at the onset of the exploration process, accurate identification of the facies and mapping their distribution over the entire reservoir is challenging. This is because not enough well data is available to calibrate and transform the seismic amplitude data based on cross plots of acoustic impedance and log-measured properties. This motivates the need to have an automated procedure to help identify possible facies from the seismic amplitude data directly and then to be able to generate maps of their probable spatial distributions using the same seismic data volume.

A seismic facies can be defined as a group of seismic amplitude variations with characteristics that distinctly differ from those from other facies. A seismic facies is the manifestation of the underlying geologic facies or structural feature in the seismic amplitude data. Different approaches can be used to search and identify these from the seismic data. These could be based on analysis of either the seismic waveforms or the seismic attributes.

Statistical classification techniques, which work on seismic attributes like amplitude, have found increasing use within traditional interpretation workflows\(^2\). The objective of these techniques is to be able to describe the variability of the data and highlight details of the underlying geologic features. Statistical classification techniques may be supervised based upon established identification rules or they may be unsupervised\(^3\), based on automated recognition of patterns in data. The most commonly used supervised technique is that of artificial neural networks\(^4\). Supervised techniques, though flexible, need substantial training effort based on available data or prior knowledge. This is usually time consuming, case