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# Integrated approach using well data and seismic attributes for reservoir characterization

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Abstract: In general, well log and core data have been utilized for reservoir characterization. These well data can provide valuable information on reservoir properties with high vertical resolution at well locations. While the seismic surveys cover large areas of field but give only indirect features about reservoir properties. Therefore it is possible to estimate the reservoir properties guided by seismic data on entire area if a relationship of seismic data and well data can be defined. Seismic attributes calculated from seismic surveys contain the particular reservoir features, so that they should be extracted and used properly according to the purpose of study. The method to select the suitable seismic attributes among enormous ones is needed. The stepwise regression and fuzzy curve analysis based on fuzzy logics are used for selecting the best attributes. The relationship can be utilized to estimate reservoir properties derived from seismic attributes. This methodology is applied to a synthetic seismogram and a sonic log acquired from velocity model. Seismic attributes calculated from the seismic data are reflection strength, instantaneous phase, instantaneous frequency and pseudo sonic logging data as well as seismic trace. The fuzzy curve analysis is used for choosing the best seismic attributes compared to sonic log as well data, so that seismic trace, reflection strength, instantaneous frequency, and pseudo sonic logging data are selected. The relationship between the seismic attribute and well data is found out by the statistical regression method and estimates the reliable well data at a specific field location derived from only seismic attributes. For a future work in this study, the methodology should be checked an applicability of the real fields with more complex and various reservoir features.

## 1. Introduction

Reservoir characterization has gained a new momentum in the past decade, largely due to the introduction of geostatistical methods to the petroleum industry and rapid progress made in their advancement. The improved understanding of a reservoir will aid in better management and better exploitation of its hydrocarbon recovery potential.

The challenge in understanding and predicting reservoir performance is two-fold: first, to describe reservoir geologic heterogeneities realistically and quantitatively, and second to model reservoir flow behaviour in the presence of all heterogeneities accurately and efficiently. While seismic data is routinely and effectively used to estimate the structure of reservoir bodies, it typically plays no role in this essential task of estimating rock or reservoir property distributes, as measured or computed form logs. In the presence of 3D seismic and logged wells, the simultaneous analysis of seismic attribute data with borehole data in an interactive environment often leads to better estimates of property distributions in comparison with estimates generated from well data alone, where the seismic data is used only for geometry information.

This paper briefly discusses the steps involved in this analysis. First, extract the seismic attributes from 3D seismic survey data. And a global prioritising technique called fuzzy curve analysis was used to select extracted attributes to correlate with log measurements. Selected attributes then served as input variables to a regression or a neural network to develop multivariate correlations with the well log measurements.

## 2. Definition of Seismic attributes

We choose to analyze not the seismic data itself but the attributes of the seismic data. One reason why we expect this to be more beneficial than the raw seismic data is that many of these attributes will be non-linear, thus increasing the predictive power of the technique. A second reason is that there is often benefit in breaking down the input data into component parts. This process is called pre-processing of feature extraction, and it can often greatly improve the performance of a pattern recognition system by reducing the dimensionality of the data before using it to train the system. Pre-processing can also provide a mean of adding prior knowledge into the design of the pattern recognition system.

We define a seismic attribute generally as any mathematical transform of the seismic trace data. This includes simple attributes such as trace envelope, instantaneous phase, and instantaneous frequency as well as complicated attributes such as seismic trace inversion and AVO. The transform may not incorporate other data sources. For example, trace inversion assumes other data sources, such as the seismic wavelet, the initial guess model, and constraints. However, for this analysis we still consider the inversion result to be an attribute of the seismic trace.

**Complex seismic trace analysis by Taner(1979)**

Transformations of data from one form to another are common in signal analysis, and various techniques are used to extract significant information from time series (seismic data). Interpreting data from different points of view often results in new insight and the discovery of relationships not otherwise evident. Analysis of seismic data as an analytic signal, complex trace analysis, is a transform technique which retains local significance. Complex trace analysis provides new insight, like Fourier transforms, and is useful in interpretation problems. Complex trace analysis effects a natural separation of amplitude and phase information, two of the quantities (call "attributes") which are measured in complex trace analysis. The amplitude attribute is called "reflection strength." The phase information is both an attribute in its own right and the basis for instantaneous frequency measurement. Amplitude and phase information are also combined in additional attributes, weighted average frequency and apparent polarity

**Calculation of the quadrature trace**

We give equivalent ways of defining $f^*(t)$ and $f(t)$, first in terms of Fourier integrals and then by convolution in time domain using the Hilbert transform. The amplitude spectrum of the complex trace vanishes for $\omega\langle 0$ and has twice the magnitude for $\omega\rangle 0$. The phase $\phi(\omega)$ is unchanged (except it is not defined for $\omega\langle 0$). The complex trace can thus be found by Fourier transforming the real trace, zeroing the amplitude for negative frequencies a doubling the amplitude for positive frequencies, and then inverse Fourier transforming. And equivalent formula for $f^*(t)$ is given by the Hilbert transform.

**Basic definitions**

Complex trace analysis treats a seismic trace $f(t)$ as the real part of an analytical signal or complex trace, $F(t) = f(t) + jf^*(t)$. The quadrature (also called conjugate or imaginary) component $f^*(t)$ is uniquely determinable from $f(t)$ if we require that $f^*(t)$ be determined from $f(t)$ by a linear convolution operation, and reduces to phasor representations if $f(t)$ is a sinusoid, that is, $f^*(t) = A\sin(\omega t + \theta)$ if $f(t) = A\cos n(\omega t + \theta)$ for all real values of $A$ and $\theta$ and all $\omega\rangle 0$.

The use of the complex trace $F(t)$ makes it possible to define instantaneous amplitude, phase, and frequency in ways which are logical extensions of the definitions of these terms for simple harmonic oscillation. Complex traces can also be used in similarity calculations, enabling us to find more precisely the relative arrival times of a common signal appearing on different traces.

The real seismic trace $f(t)$ can be expressed in terms of a time-dependent amplitude $A(t)$ and a time dependent phase $\theta(t)$ as

$$f(t) = A(t)\cos\theta(t) \tag{1}$$

The quadrature trace $f^*(t)$ then is

$$f^*(t) = A(t)\sin\theta(t) \tag{2}$$

and the complex trace $F(t)$ is

$$F(t) = f(t) + jf^*(t) = A(t)e^{j\theta(t)} \tag{3}$$

If $f(t)$ and $f^*(t)$ are known, one can solve for $A(t)$ and $\theta(t)$:

$$A(t) = [f(t)^2 + f^{*2}(t)]^{1/2} = |F(t)] \tag{4}$$

and

$$\theta(t) = \tan^{-1}[f^*(t)/f(t)] \tag{5}$$

$A(t)$ is called "reflection strength", and $\theta(t)$ is called "instantaneous phase".

The rate of phase change o the time-dependent phase gives a time-dependent frequency

$$\frac{d\theta(t)}{dt} = \omega(t) \tag{6}$$

A more convenient way of computing the instantaneous frequency is to compute the derivative of the arctangent function itself

$$\omega(t) = \frac{d}{dt}\{\tan^{-1}[f^*(t)/f(t)]\} \tag{7}$$

which results in

$$\omega(t) = \frac{f(t)\frac{df^*(t)}{dt} - f^*(t)\frac{df(t)}{dt}}{f^2(t) + f^{*2}(t)} \tag{8}$$

where the derivatives of $f(t)$ and $f^*(t)$ can be computed in convolutional form.

We also define a weighted average frequency $\bar{\omega}(t)$ as

$$\bar{\omega}(t) = \frac{\int_{-\infty}^{\infty} A(t-\tau)\omega(t-\tau)L(\tau)d\tau}{\int_{-\infty}^{\infty} A(t-\tau)L(\tau)d\tau} \tag{9}$$

where $L(\tau)$ is a low-pass filter. Apparent polarity is defined as the sign of $f(t)$ when $A(t)$ has a local maximum. Positive or negative sign is assigned assuming a zero-phase wavelet and a positive or negative reflection coefficient, respectively.

With the success of 3D surveys has come the popularity of seismic attributes. Attributes are valuable for gaining insight from the data particularly when displayed spatially over interpreted horizons. However, all the man attributes available are not independent pieces of information but, in fact, simply represent different ways of presenting a limited amount of basic information. The key to success lies in selecting the most applicable attribute for the problem. Furthermore, statistical analysis using attributes must be based on understanding, not simply mathematical correlation. Attributes are related to the fundamental information in seismic data: time, amplitude, frequency, and attenuation. Most of the attributes we use are post-stack. The pre-stack attributes are principally derived from amplitude variations with offset (AVO) measurements.

Horizon attributes are extracted along a tracked horizon and thus benefit from the precision of machine autotrackers. The positional precision is typically around a quarter of a millisecond and the precision of the attribute value somewhat comparable. Windowed attributes, on the other hand, use the sample values at, for example, 2 or 4 ms intervals. They may add up or average all the sample values to give a gross attribute, they may select one unique attribute value, or a distribution or trend in the attribute values over the window may be calculated.

Time-derived attributes help to discern structural detail. Amplitude-derived and frequency-derived attributes address problems for stratigraphy and reservoir properties. Amplitude attributes are here the most robust and useful, but frequency attributes may help reveal additional geologic layering. The hybrid attributes are particularly interesting because they contain elements of amplitude and frequency, and thus useful measurements of seismic character.

Petrophysical studies and seismic modelling, of course, are other sources of understanding. Such understanding is necessary to build confidence in observed correlations with reservoir parameters and must be part of all attribute analysis projects.

## 3. Methodology

Seismic guided estimation of rock or reservoir fluid properties measured by or computed from logs requires a systematic multi-step analysis, which is subsequent to normal processing of the seismic and log data. The objective is to identify which seismic attributes in a given dataset correlate well to which log properties, and then to use those attributes to assist the log property mapping.

After extracting seismic attributes from 3D seismic survey, the step that is selecting the best seismic attributes is needed. Sine using all attributes is computationally unfeasible and labour intensive, fuzzy logic is used to select the most statistically significant attributes for developing regression equations for individual reservoir properties. And then we can integrate seismic attributes and log properties. In the linear mode, the regression methods are used. But non-linear regressions were used, as individual attributes had low correlation coefficients when cross-plotted with log properties, and neural network architectures were developed to relate the selected attributes to each property.

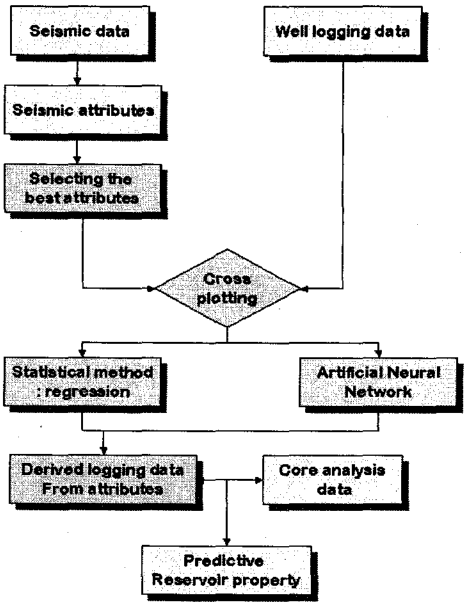



Fig. 1. Flow chart of methodology.

**Fuzzy curve analysis**

We use fuzzy curves for identification of the significant input variables. Consider a multiple-input, single-output system for which we have input-output data with possible extraneous inputs. We wish to determine the significant inputs. We call the input candidates $x_i (i = 1,2,...,n)$, and the output variable $y$. Assume that we have $m$ data points available and that $x_{ik} (k = 1,2,...,m)$ are the $ith$ coordinates of each of the $m$ data points. For each input variable $x_i$, we can plot the $m$ data points in $x_i - y$ space. And for every point $(x_{ik}, y_k)$ in $x_i - y$ space, we draw a fuzzy membership function for the input variable $x_i$ defined by

$$F_{ik}(x_i) = \exp(-(\frac{x_{ik} - x_i}{b})^2), \qquad k = 1,2,3,...m. \tag{10}$$

Each pair of $F_{ik}(x_i)$ and the corresponding $y_k$ provides a fuzzy rule for $y$ with respect to $x_i$. The rule is represented as "if $x_i$ is $F_{ik}(x_i)$, then $y$ is $y_k$." $F_{ik}(x_i)$ is the input variable fuzzy membership function for $x_i$ corresponding to the data point $k$. $F_{ik}(x_i)$ can be any fuzzy membership function, including triangle, trapezoidal, Gaussian, and others. Here we use Gaussians. We typically take $b$ as about 10% of the length of the input interval of $x_i$. For $m$ data points, we have $m$ fuzzy rules for each input variable.

We use centroid defuzzification to produce a fuzzy curve $FC_i$ for each input variable $x_i$.

$$FC_i(x_i) = \left(\frac{\sum_{k=1}^{m} F_{ik}(x_i) \bullet y_k}{\sum_{k=1}^{m} F_{ik}(x_i)}\right) \tag{11}$$

If the fuzzy curve for given input is flat, then this input has little influence in the output data and it is not a significant input. And if the range of a fuzzy curve is about the range of the output data $y$, then the input candidate $x_i$ is important to the output variable. The fuzzy curve tells us that the output is changing when $x_i$ is changing. We rank the importance of the input variables $x_i$ according to the range covered by their fuzzy curves.

**Linear regression (Statistical method)**

Next step is to determine a relationship between seismic attributes and log properties. Given a particular attribute of the seismic data, the simplest procedure for deriving the desired relationship between log properties and seismic attribute is to cross-plot the two. The assumption is that the target log has been integrated to travel-time at the same sample rate as the seismic attribute. Effectively, this integration reduces the target log to the same resolution as the attribute, which is usually significantly coarser than the log property. Each point in the cross-plot consists of a pair of numbers corresponding to a particular time sample.

The extension of the conventional linear analysis to multiple attributes (multivariate linear regression) is straightforward. Assume, for simplicity, that we have three attributes. At each time sample, the target log is modelled by the linear equation.

$$L(t) = \omega_0 + \omega_1 A_1(t) + \omega_2 A_2(t) + \omega_3 A_3(t) \tag{12}$$

The weights in this equation may be derived by minimizing the mean-squared prediction error, as extended from equation (13)

$$E^2 = \frac{1}{N}\sum_{i=1}^{N}(L_i - \omega_0 - \omega_1 A_{1i} - \omega_2 A_{2i} - \omega_3 A_{3i})^2 \tag{13}$$

Note that the linear requirement may be relaxed somewhat by applying a non-linear transform to either the target data or the attribute data or both. And several limitations inhibit multivariate regression techniques, many arising from the inexact nature of the relationship between petrophysical variables. Conventional parametric regression requires a priori assumptions regarding functional relationships between the independent and dependent variables. Complex underlying physical relationships are not known in advance, making traditional multiple regression techniques inadequate, leading to biased estimates. Non-parametric transformations, however, generate regression relations in a flexile data-defined manner and in doing so let the data itself suggest the functionalities. They have been developed to offer a much more flexible data analysis tool when exploring the underlying relationship between independent and dependent variables.

The non-parametric regression approach proposed by Breiman and Friedman, and refined by Xue, et al, provides exactly such a "non-biased" mechanism for the purpose of establishing the minimum error relationship between the dependent and independent variables. The method of Alternating Conditional Expectation (ACE) is based on the concept of developing an optimal transformation of each variable-both the dependent variable, as well as the independent variable(s)

**Non-linear regression (Artificial neural network)**

A neural network is a series of layers with nodes and weights that represent complex relationships among input and output variables. The first layer has input nodes representing the input variables (independent variables) specified by the problem. The node of a hidden layer uses the sum of the weighted outputs of previous layer and sigmoid function to provide output for the nodes in the subsequent hidden layer. The number of nodes in each layer and the weights are determined by trials and by optimisation. The objective of the neural network is to obtain optimal weights to give a best value for the nodes (the dependent variable) of the output layer.

The advantages of neural network approach are several. It does not require an explicit functional relationship between the input and output variables. It can be trained from past available data to learn and approximate the non-linear relationships to any degree of accuracy. It is applicable to multivariate systems. One of the significant drawbacks of neural network approach is the input nodes must be specified a priori. The type of input variables and the optimal number of input variables can not easily be determined from neural network analysis,

## 4. Results

The methodology suggested in this paper is applied to a synthetic velocity model. Fig.1 is a velocity map showing the locations of the development wells and test locations. The wells are located at 1000m(well A), 2000m(well B), 2500m(well C), and 3500m(well D) The test locations are located at 1500m(T#1) and 3000m(T#2).

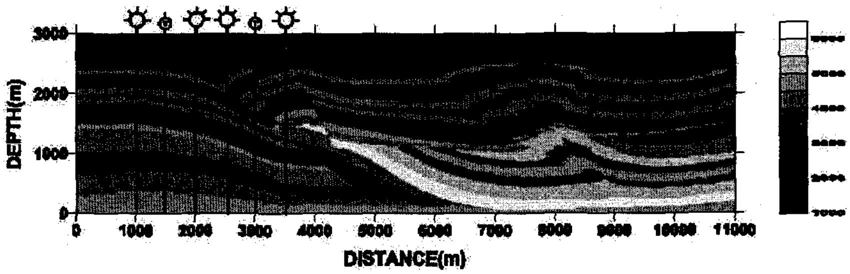



Fig. 2. Synthetic velocity model.

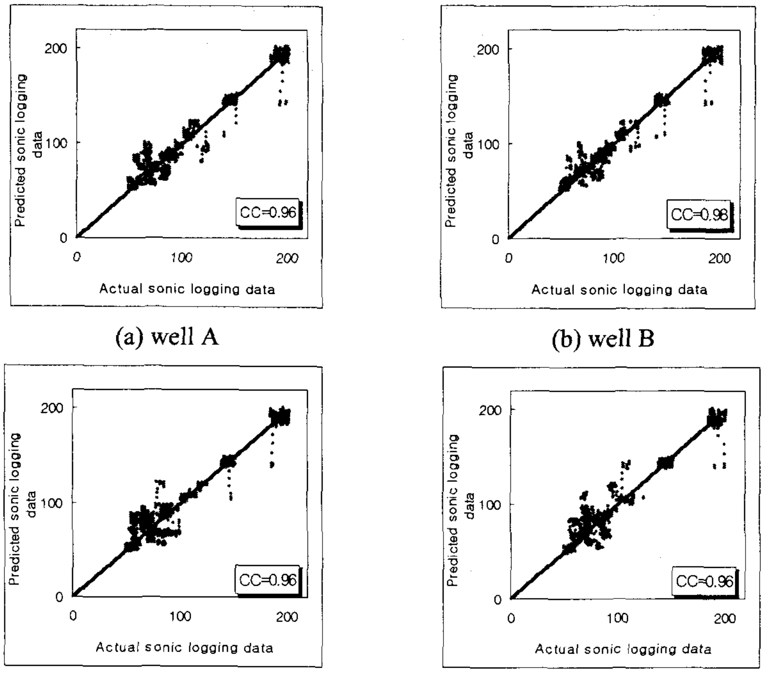
We can extract the seismic attributes such as seismic trace, reflection strength, pseudo sonic logging data, instantaneous phase and instantaneous frequency from each well. And fuzzy curve analysis is used to select the best describing data among these attributes. Table.1 is the result of fuzzy curve analysis. Well A and B are grouping to group Ⅰ and well C and D are group Ⅱ, so T#1 can be derived from the results of group Ⅰ and T#2 from group Ⅱ.

Table 1. Sonic well logs versus Seismic attributes fuzzy ranking.

| Well site | Attributes | Range | CC | Rank |
|---|---|---|---|---|
| I | Seismic trace | 0.54 | 0.90 | 1.45 |
| | Reflection strength | 0.55 | 0.93 | 1.48 |
| | Pseudo sonic log | 0.92 | 0.99 | 1.91 |
| | Instantaneous phase | 0.26 | -0.73 | 0.99 |
| | Instantaneous frequency | 0.20 | 0.87 | 1.09 |
| Ⅱ | Seismic trace | 0.59 | 0.92 | 1.51 |
| | Reflection strength | 0.57 | 0.94 | 1.51 |
| | Pseudo sonic log | 0.92 | 0.99 | 1.91 |
| | Instantaneous phase | 0.28 | -0.81 | 1.09 |
| | Instantaneous frequency | 0.27 | 0.95 | 1.22 |

As shown in Table.1, we can use seismic trace, reflection strength, pseudo sonic log, and instantaneous frequency as seismic attributes.

These selected attributes and well logging data (sonic logging data) can be made the relationship by using multiple regressions in each group. To recognize how well predicted sonic logging data from relationship can be similar with sonic logging data, we are cross-plotting these two data. The results are presented in Fig. 3. The correlation coefficient at well A is 0.96(0.98 at well B, 0.96 at well C, and 0.96 at well D). As a result, we can know the relationship is valid which is derived from multiple regressions and describe the distribution of predicted sonic logging data.

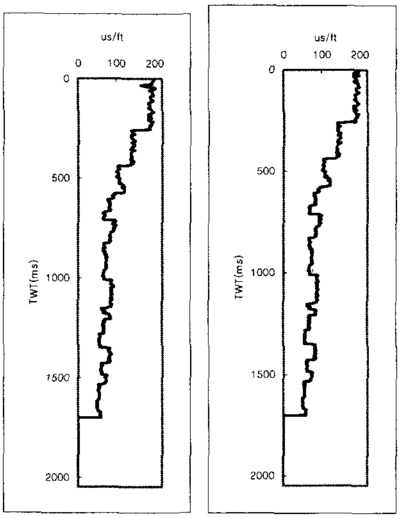



(a) well A (b) well B

(c) well D (d) well D

Fig. 3. Cross-plotting of predicted and actual sonic logging data at wells.

Fig. 4 is predicted sonic logging data at T#1 and T#2 from each relationship and Fig. 5 is a map of predicted sonic logging data and it is correspond to 0m from 4000m.




(a) Test #1 (b) Test #2

Fig. 4. Predicted sonic logging data at test locations.

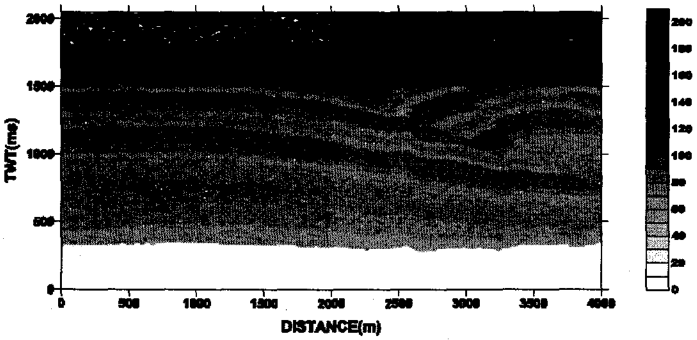



Fig. 5. Predicted sonic logging data of entire study area.

## 5. Summary

This paper suggests the methodology which would be estimated the reservoir property by integrating the seismic attributes and well data. Before the seismic attributes and well data are integrated, stepwise regression or fuzzy curve analysis can be used for selecting the best describe attributes. And then we can integrate the well data and selected seismic attributes, and find out their relationship. To know the relationship we can use statistical method such as regression or artificial neural network method properly. According to this methodology we can apply to a synthetic velocity model. We can use these seismic attributes such as seismic trace, reflection strength, instantaneous frequency, and pseudo sonic logging data for integrating well logging data (sonic logging) with. Relationship between well logging data and selected attributes can be presented by multiple regressions, and the predicted well logging data are similar with actual well logging data. Therefore, it is possible to predict the reservoir property guided by seismic attributes if a relationship of seismic attributes and well data can be defined.

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