Modeling Uncertainty in Seismic Imaging of Reservoir Structure

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1. Introduction

The modeling of structurally complex reservoirs is one of the most difficult tasks in reservoir modeling. The difficulty in characterizing complex structural geometry is mainly attributed to the large uncertainty in seismic images resulting from the limited quality/resolution of seismic data. The uncertainty in seismic velocity is an example of the source of such uncertainty. Inaccurate seismic velocity model produces inaccurate migration of seismic images, and consequently, an inaccurate positioning of fault location/geometry. Despite the structural uncertainty associated with seismic imaging and the risk in relying on deterministic structural models, reservoir models are rarely constructed from more than one seismic image. Seismic processing and interpretation are too time consuming to interpret multiple seismic data sets. Instead, a single processed seismic image is interpreted. From this single structural interpretation, an uncertainty model is built by perturbing fault and horizon location (Ref. 1). However, this type of uncertainty analysis completely ignores the uncertainty of the images itself, which may be of greater importance, in many practical cases, than the uncertainty modeled from a single structural interpretation. One of the consequences is that, in structurally complex reservoirs, it is very difficult to obtain a history match of production data, because the prior structural uncertainty is too small. The location and geometry of faults, which are known to exert strong impact on fluid flow behavior especially in water (or gas) drive recovery process, is usually fixed. Other parameters, such as fault transmissibility or facies properties, are then forced to compensate for the “wrong” structural model. Moreover, poorly identified fault location can easily mislead future development planning since the distribution of bypassed oil is often controlled by faults.

A desirable approach for overcoming this problem is a structural uncertainty modeling based on the uncertainty assessment of seismic imaging. This is achieved by obtaining multiple alternative seismic images, from which multiple alternative structural models are obtained. Recently, Clapp (2003 Ref.2, 2001 Ref.3) proposed a methodology for assessing the uncertainty in seismic velocity in the processing of raw seismic data. By accounting for this uncertainty and by inputting multiple velocity models into the migration of seismic data, multiple seismic data/image sets were obtained. Structural models interpreted on the resulting multiple seismic images can be used as a set of prior reservoir
models for history matching problem, providing prior information on structural uncertainty. By evaluating posterior structural uncertainty through the incorporation of production data, the fully integrated assessment of the structural uncertainty would be achieved, hopefully assisting in the risk evaluation in future development planning. In order to make such an application feasible, an efficient and robust algorithm for automatic seismic interpretation is required since manual structural interpretation on dozens of seismic images is usually impossible.

This report outlines a methodology and some preliminary results of the structural uncertainty modeling proposed by the joint research project between SCRF (Stanford Center Reservoir Forecasting) and SEP (Stanford Exploration Project). In this paper, we propose a modeling strategy which consists of 1) obtaining multiple seismic images through the quantification of uncertainty of seismic velocity, and 2) a new method for automatic seismic interpretation. The creation of multiple seismic data set is carried out by applying the method of Clapp (Ref. 2). Automatic seismic interpretation is performed using SIMPAT simulation (Arpat, 2005 Refs. 4~6). Both of the methodologies are reviewed/discussed in Section 2. Section 3 presents the results of a synthetic reservoir application.

2. Method

2.1. Multiple Seismic Imaging Assessing Velocity Uncertainty: Review

In this research, the uncertainty in seismic imaging is modeled using the method of Clapp (1-D super Dix, Ref.2) by focusing on the uncertainty in seismic velocity. This section briefly describes the methodology of Clapp using the example from Ref.2. Although the methodology is used in a classical ray-based tomography problem in the original paper (Ref.2), this example explains general application.

The figures shown below demonstrate the typical velocity estimation procedure from CMP gather.

The left figure shows an example of CMP gather (traveltime vs. offset) obtained at particular common midpoint. Assuming waves as expanding circles, the relation between traveltime and offset is described as:

\[ t^2 = \tau^2 + \frac{4h^2}{v_{RMS}^2} \]  

\( t \): two-way traveltime (i.e. traveltime from source to receiver)  
\( \tau \): zero-offset two-way traveltime (called ‘traveltime depth’)  
\( h \): offset  
\( v_{RMS} \): root-mean-square (RMS) velocity

Assuming a horizontally layered velocity field where the velocity of each layer is defined as interval velocity \( (v_{int}) \), RMS velocity \( (v_{RMS}) \) in Eq.(1) is defined as below:

\[ v_{RMS,i}^2 = \frac{\sum_{j=1}^{1} v_{int,j}^2 \Delta \tau_j}{\sum_{j=1}^{1} \Delta \tau_j} \quad (i = 1,2,\ldots, N) \]  

\( \Delta \tau \) in Eq.(2) is layer thickness in traveltime depth, which is related to physical layer thickness \( \Delta z \) as:

\[ \Delta \tau = \frac{2\Delta z}{v_{int}} \]
According to Eq.(1), the amplitude shown in the CMP gather is regarded as a collection of hyperbola curves which are characterized by traveltime depth and corresponding RMS velocity at individual reflection points. The actual relation between traveltime and offset is not exactly hyperbolic since wave propagation is not precisely circular in laterally heterogeneous velocity field. However, it is an usual practice to estimate RMS velocity using this hyperbolic approximation. The velocity scan (center figure) for estimating RMS velocity is generated from the CMP gather by taking the summation of amplitude along each hyperbola curve, then plotting that sum in a traveltime depth vs. RMS velocity plane. On the velocity scan, we observe a peak of strong amplitude responses which indicates the RMS velocity corresponding to reflection point at traveltime depth $\tau$. The RMS velocity is estimated as a function of $\tau$ by auto-picking the maximum amplitude response on the velocity scan (dashed line in the center figure). The interval velocity ($v_{\text{int}}$, dashed line in the right figure) is calculated from the auto-picked RMS velocity using the relationship expressed in Eq.(2).

However, amplitude response peak usually shows considerable spread on the velocity scan, which indicates that the auto-picked RMS velocity is uncertain. This uncertainty is attributed to the noise of seismic data and the limited applicability of hyperbolic approximation. Clapp (Ref. 2~3) proposed to generate equi-probable multiple realizations of the velocity as a function of depth, instead of obtaining a single best-estimate velocity model. The multiple velocity models are then used to produce equi-probable migrations of the seismic data. The methodology takes the following procedure.

1) Auto-picking of RMS velocity and evaluation of error variance

The first step is to obtain the RMS velocity from the velocity scan by auto-picking, and to evaluate the error variance of the RMS velocity from the velocity scan. The error variance $\sigma^2_v(\tau)$ at traveltime depth $\tau$ is evaluated as,

$$\sigma^2_v(\tau) = \frac{\int \left[ v_{\text{RMS}} - v_{\text{RMS, auto_pick}} \right]^2 s(\tau) d v_{\text{RMS}}}{\int s(\tau) d v_{\text{RMS}}}$$

where $v_{\text{RMS, auto_pick}}(\tau)$ is the auto-picked RMS velocity at traveltime depth $\tau$, $s(\tau)$ is the semblance (amplitude stacked along each hyperbola) plotted on the velocity scan. In actual application, $\sigma^2_v(\tau)$ is calculated in a discretized form of Eq.(4). The example of the evaluated auto-picked RMS velocity and the square-root of error variance is depicted below.
2) Construction of the inversion problem

The interval velocity $v_{\text{int}}$ is obtained from the auto-picked RMS velocity $v_{\text{RSM}}$ using the relation in Eq.(2). In principle, it is possible to directly solve for $v_{\text{int}}$ by inverting the linear system in Eq.(2). However, in practice, the auto-picked RMS velocity curve shows considerable small scale fluctuation, often due to noise in the data. Since the interval velocity is a function of derivative of the RMS velocity, the direct calculation of $v_{\text{int}}$ from noisy $v_{\text{RSM}}$ by simply relying on the solution of a linear system would produce an erroneous interval velocity model.

One of the solutions to avoid a solution of Eq.(2), which is noisy, is to add a regularization constraint to Eq.(2) to smooth the modeled interval velocity. In other words, one tries to obtain an interval velocity model which has a given desired smoothness and also best fits to the auto-picked RMS velocity. This is achieved by solving an inversion problem, where as input data the auto-picked RMS velocity $v_{\text{RSM}}$ is used and a target model is the interval velocity $v_{\text{int}}$. This inversion problem is constructed based on Eq.(2) and also uses the error variance $\sigma_v^2$ of Eq.(4) in order to account for the uncertainty in auto-picked $v_{\text{RSM}}$. This is done as follows:

Eq.(2) is rewritten as follows by specifying $\Delta \tau_j = \Delta \tau$ (constant):

$$v^2_{\text{RMS},i} = \frac{1}{\tau} \sum_{j=1}^{N} v^2_{\text{int},j} \quad (i = 1, 2, \ldots, N) \quad (5)$$

Using Eq.(5) as a forward model, the misfit of $v^2_{\text{RMS},i}$ between that obtained from the auto-picked RMS velocity (data), $v^2_{\text{RSM,auto_pick},i}$, and that derived from the interval velocity to be inverted (model), $v^2_{\text{int,i}}$, is evaluated as:
\[ r_i = \sigma^2_{v,i} - \frac{1}{i} \sum_{j=1}^{i} \sigma^2_{v,ij} = \frac{1}{i} \left( \sigma^2_{v,i} - \sum_{j=1}^{i} \sigma^2_{v,ij} \right) \left( i = 1, 2, \ldots, N \right) \]  

(6)

For simplicity, the auto-picked RMS velocity \( v_{RSM,auto\_pick,i} \) will be denoted as \( v_{RSM,i} \) hereafter. The residual \( r_{n,i} \) to be minimized in the inversion problem is defined from the misfit \( r_i \) (Eq.(6)) and the error variance \( \sigma^2_{v,i} \) (Eq.(4)) as follows:

\[ r_{n,i} = \frac{r_i}{\sigma^2_{v,i}} = \frac{1}{\sigma^2_{v,i}} \left( \sigma^2_{v,i} - \sum_{j=1}^{i} \sigma^2_{v,ij} \right) \left( i = 1, 2, \ldots, N \right) \]  

(7)

The minimization of the residual \( r_{n,i} \) accounts for the data uncertainty in \( v_{RSM,i} \) in obtaining the best-fit model, i.e., since \( r_i = \sigma^2_{v,i} r_{n,i} \) from Eq.(7), a large misfit \( r_i \) is allowed for a large error variance \( \sigma^2_{v,i} \) and vice versa.

Eq.(7) is written in matrix form as,

\[ r_n = \Sigma D_1 \left( T v_{RSM}^2 - C v_{int}^2 \right) \]  

(8)

where:

\[ r_n^T = [r_{n,1}, r_{n,2}, \ldots, r_{n,i}, \ldots, r_{n,N}] \]

\[ v_{RSM}^2 = \left[ v_{RSM,1}^2, v_{RSM,2}^2, \ldots, v_{RSM,i}^2, \ldots, v_{RSM,N}^2 \right] \]

\[ v_{int}^2 = \left[ v_{int,1}^2, v_{int,2}^2, \ldots, v_{int,i}^2, \ldots, v_{int,N}^2 \right] \]

\[ T^T = [1, 2, \ldots, i, \ldots, N] \]

\( \Sigma \): diagonal matrix whose diagonal element is \( 1/\sigma^2_{v,i} \)

\( D_1 \): diagonal matrix whose diagonal element is \( 1/T_i \)

\( C \): lower triangular matrix with the elements of 1 (causal integration)

A regularization term, whose purpose is to generate smooth inverted \( v_{int} \), is added to the problem as:
\[ \mathbf{r}_m = D\mathbf{v}_{\text{int}} \]

By minimizing \( \mathbf{r}_n \) and \( \mathbf{r}_m \) jointly using the least square optimization, the maximum likelihood solution of the interval velocity \( \mathbf{v}_{\text{int}} \) is obtained. This is done through the minimization of,

\[ 0 \approx \|\mathbf{r}_n\|^2 + \epsilon^2 \|\mathbf{r}_m\|^2 \]

(10)

where \( \epsilon \) is a scaling weight.

3) Generation of multiple realizations of interval velocity

The next step is to generate multiple realizations of interval velocity \( \mathbf{v}_{\text{int}}^{(l)} \) based on the maximum likelihood model \( \mathbf{v}_{\text{int}}^{(0)} \) obtained from Eq.(10). This is achieved through generating multiple residual vectors \( \mathbf{r}_n^{(l)} \) which have the same covariance structure as that of the initial residual vector \( \mathbf{r}_n^{(0)} \) obtained from \( \mathbf{r}_n^{(0)} = \Sigma \mathbf{D}_1 \left( \mathbf{T} \mathbf{v}_{\text{RMS}} - \mathbf{C} \mathbf{v}_{\text{int}}^{(0)^2} \right) \). For this purpose, a filter matrix \( \mathbf{H} \) is constructed based on a method of prediction error filter (PEF, see Ref. 8 for details).

The important property of the filter matrix \( \mathbf{H} \) is: if we apply the filter matrix \( \mathbf{H} \) to the initial residual vector \( \mathbf{r}_n^{(0)} \), we obtain white noise vector \( \mathbf{y}^{(0)} \) as output (see Ref. 8 for proof and method for obtaining \( \mathbf{H} \)). Inversely, if we apply the inverse of the matrix \( \mathbf{H} \), i.e. \( \mathbf{H}^{-1} \), to an arbitrary chosen white noise vector \( \mathbf{y}^{(l)} \), we obtain a new residual vector \( \mathbf{r}_n^{(l)} \), which exhibits the same covariance structure as the initial residual vector \( \mathbf{r}_n^{(0)} \).

Therefore, introducing the filter matrix $H$, Eq.(8) is rewritten as:

$$\mathbf{y} = H \mathbf{r}_n = H \Sigma D_1 \left( T v_{\text{RMS}}^2 - C v_{\text{int}}^2 \right)$$

(11)

The vector $\mathbf{y}$ in Eq.(11) is white noise. The multiple realizations of interval velocity $v_{\text{int}}^{(i)}$ are generated by substituting $\mathbf{y}$ by a series of randomly chosen white noise vectors $\mathbf{y}^{(i)}$, and solving Eq.(11) for $v_{\text{int}}$. Due to the property of prediction error filter, the covariance structure of the residual vector is preserved. The corresponding multiple RMS velocity models $v_{\text{RMS}}^{(i)}$ are calculated from $v_{\text{int}}^{(i)}$ using Eq.(5).

Using the multiple velocity models $v_{\text{RMS}}^{(i)}$, multiple seismic data sets are obtained by migrating raw seismic data, and then depth-converted using $v_{\text{int}}^{(i)}$.

The migration takes considerable CPU time (much greater than any other reservoir modeling process such as geostatistical or flow simulation). This is because, while geostatistical simulation operates only on the physical model space (i.e. 3D at most), migration operates both on data and model space increasing the dimensionality of the problem. For example, a 3D poststack migration calls for 5-dimensional nested loops and could take several days of CPU time (for each migration). Adding the uncertainty in velocity to the problem adds one more loop. Furthermore, the volume of seismic data/image is generally much larger than the volume of reservoir model grid.

### 2.2. Automatic Seismic Interpretation Using SIMPAT

Aside from the CPU cost of migration, the manual labor cost of seismic interpretation is also one of the primary factors that prevent the use of multiple seismic data sets from being practical. Since manual interpretation is time consuming especially when the volume of data is large, it is essential to automate the interpretation process in order to build dozens of structural models from various seismic images. Unfortunately, commercially available automatic interpretation tools are hardly applicable for structurally complicated reservoirs since most algorithms rely on a simple auto-tracking of amplitude peaks. For that reason, the need for a robust and efficient automatic seismic interpretation method arises.

Recently, a pattern-based geostatistical sequential simulation (SIMPAT) algorithm was proposed by Arpat (2005, Ref. 4–6) by constructing reservoir facies models simulating patterns. The algorithm is designed to simulate facies or petrophysical property model using training image as prior model for the spatial pattern of the variable being simulated. Although SIMPAT algorithm is originally
developed for pattern simulation/conditioning problems for characterizing geological objects such as fluvial channels, it also has a potential for the application to automatic seismic interpretation problem by the following reasons.

1) The SIMPAT algorithm is built on multi-scale pattern recognition technique. In fact, this process is quite similar to horizon/fault picking in manual seismic interpretation process, since manual horizon picking is done based on visual inspection of the ‘patterns’ of reflections rather than the mere tracking of amplitude peaks.

2) The similarity evaluation method used in SIMPAT algorithm works better for filtered training image (Ref. 9). Considering that a seismic amplitude image is virtually an illustration of naturally filtered horizons, the problem is suitable to SIMPAT algorithm.

Thus we propose to use SIMPAT algorithm as a tool for automatic seismic interpretation. This section briefly reviews SIMPAT algorithm first, then describes the proposed approach for automatic interpretation next.

2.2.1 SIMPAT Algorithm with Soft Data Conditioning: Review

The automatic seismic interpretation problem is categorized as a “soft data conditioning” problem amongst the algorithms covered by SIMPAT. Thus this review focuses on how soft data conditioning is performed by SIMPAT (Ref. 6).

Consider the problem to simulate fluvial channel using seismic image as conditioning data. This problem is called “soft data conditioning” problem since the simulated geological object will be conditioned to the soft (secondary) information from seismic image rather than to the direct (hard) information such as well observation. The soft data conditioning problem uses a set of two types of training images, i.e. “hard training image” and “soft training image”. In this example, the hard training image is an illustration of fluvial channel which describes the desired pattern of channel objects to be simulated. This hard training image can be taken from geological analog, can be purely conceptual, or can be an unconditional Boolean realization. The soft training image is a seismic image obtained by forward-modeling the seismic data on the hard training image. It can be as simple as a moving average of the hard training image or as complex as the result of full seismic wave modeling.

The patterns of hard variable (e.g. channel object) and soft variable (e.g. seismic amplitude), which are observed on the hard and soft training images, are related to each other and stored in the pattern database. An example of pattern database construction is as shown below:
As depicted in the figure, both training images are scanned by a template window to extract the pattern of objects. The hard image pattern and the soft image pattern extracted at the collocated grid node are coupled and stored in the pattern database as a pair of hard and soft patterns. Thus the constructed pattern database can be considered as a training database which stores the information about pattern-to-pattern correlation observed between hard and soft training image.

Using the constructed pattern database, channel objects are simulated conditioning to actual seismic data. The actual seismic data is denoted as “soft data” in SIMPAT. The procedure takes sequential simulation algorithm; i.e., visiting nodes on simulation grid one after another, following a random path. However, the methodology simulates channel objects as a “pattern” using the template window, instead of simulating facies in single grid node. The procedure takes the following steps:
1. Visit empty grid node \( u \) and place the template window there. Extract the pattern of previously simulated objects within the template window. Denote this (hard) pattern as \( \mathbf{hd}(u) \).

2. Extract the pattern of the soft data at node \( u \) by placing the template window on the collocated soft data grid. Denote this (soft) pattern as \( \mathbf{sft}(u) \).

3. Search the pattern database and find a joint pair of hard and soft patterns (\( \mathbf{hpat}, \mathbf{spat} \)) such that 1) whose hard pattern (\( \mathbf{hpat} \)) is as similar to \( \mathbf{hd}(u) \) as possible and 2) whose soft pattern (\( \mathbf{spat} \)) is also as similar to \( \mathbf{sft}(u) \) as possible. The similarity between the patterns \( \mathbf{a} \) and \( \mathbf{b} \), where \( \mathbf{a} \) and \( \mathbf{b} \) are expressed as vectors whose elements are grid values filled in the template window, is evaluated using Manhattan distance as below:

\[
d(\mathbf{a}, \mathbf{b}) = \| \mathbf{a} - \mathbf{b} \| \tag{12}\]

The smaller distance \( d(\mathbf{a}, \mathbf{b}) \) indicates to the greater similarity between \( \mathbf{a} \) and \( \mathbf{b} \). Therefore, the pair of patterns (\( \mathbf{hpat}, \mathbf{spat} \)) which best matches to \( \mathbf{hd}(u) \) and \( \mathbf{sft}(u) \) is found by searching the pattern database for the pair of (\( \mathbf{hpat}, \mathbf{spat} \)) which shows the minimum value of

\[
w_1 d(\mathbf{hpat}, \mathbf{hd}(u)) + w_2 d(\mathbf{spat}, \mathbf{sft}(u)), \text{ for some user-specified weights } w_1 \text{ and } w_2,
\]

4. Paste the best-matched pattern \( \mathbf{hpat} \) to the template window location at grid node \( u \).

5. Go to another empty grid node and repeat steps 1~4 until the entire grid is simulated.

The numerous implementation details are discussed in Arpat (Ref.6, 2005). Notice that, at the early stage of the simulation, a pattern is determined mostly based on the matching of the soft patterns, i.e. \( \mathbf{spat} \) and \( \mathbf{sft}(u) \), since at this stage the previously simulated patterns are few. Thus the algorithm first draws the rough framework of channel pattern mostly conditioning to the soft data, and then eventually fills the gaps of simulated patterns accounting for previously simulated objects.

Naturally, a larger template captures the pattern of geological variability better. However, the large template size requires considerable CPU time, and also requires large size of hard and soft training images in order to extract large enough numbers of pattern pairs to construct meaningful pattern database. In order to avoid this problem, SIMPAT algorithm adopts multiple-grid approach using dual templates: That is, first simulate on coarse grid using a coarse (primal) template, and then simulate on refined grid using refined (dual) template (See Ref.6 for details).
2.2.2 Application of SIMPAT for Automatic Interpretation

The figure shown below schematically illustrates the proposed method for automatic seismic interpretation using SIMPAT.

As depicted in the figure, we arbitrarily select one seismic image (denoted as ‘image 1’) from the set of multiple images provided by the method described in Section 2.1. The selected seismic image is utilized for manual structural interpretation by an expert. This image is termed “soft training image” in SIMPAT. The result of the manual seismic interpretation (structural model) from the soft training image is converted to a categorical pixelized image that depicts horizons and faults, and is used as “hard training image” in SIMPAT. Our goal is to obtain the new structural images from the other seismic images (image 2~), by conditioning the horizons and faults to the pattern of reflections observed in these seismic images. This is achieved by performing SIMPAT simulation using new seismic images (image 2~) as “soft data” together with soft and hard training images.

The advantage of SIMPAT simulation over conventional auto-horizon-picking can be explained as follows: Since the conventional auto-picking tool merely tracks amplitude peaks to pick horizons, it does not include any learning process in the automated modeling procedure. However, with SIMPAT, we use the seismic image and the corresponding structural model as a pair of soft and hard training images. This training image pair serves as ‘teacher’s interpretation’ which informs how experts correlate the continuity of amplitude to horizon and discontinuity to faults. Therefore, since SIMPAT
simulation is virtually an image processing which is performed by mimicking pattern-to-pattern
correlation tendency that appears on the training image pair, the simulated structural model would be
more realistic than conventional auto-picking result in terms of resemblance to human interpretation.

3. Synthetic Reservoir Application

3.1. Model Description

The synthetic reservoir model used in this study is constructed based on an actual reservoir data
from the North Sea. The model is a two dimensional cross-sectional model consisting 680*340 grid
blocks, 3400m in horizontal direction and 850m in vertical direction. The grid block size is 5m in
horizontal and 2.5m in vertical. The depth of reservoir is 2270 ~ 3120 m-TVDSS. Fig.1 and Fig.2
show the facies distribution and net-to-gross ratio, i.e. (net sand thickness in gridblock)/(gross
gridblock thickness), distribution of the reservoir model. The reservoir is faulted sand stone reservoir
with thin shale layers and tiny calcite bodies (Fig.1). The upper and lower part of the reservoir is shaly
sand while the middle part of the reservoir is clean sand embedded by discontinuous thin calcite
bodies. Porosity and permeability was geostatistically populated with the constraint of geological
maps as depicted in Figs.3 and 4. Average porosity and permeability are 0.24 and 537 mD,
respectively. Water saturation distribution (Fig.5) was modeled with OWC at 2688.5 m-TVDSS and
capillary transition using J-function from the porosity and permeability realization. The fluid densities
are obtained from the field data. The reservoir is modeled as undersaturated reservoir without gas cap.
The water saturation of shale and calcite bodies is specified as 1.0.

The rock physics properties are modeled based on the petrophysical properties model. Fig.6
depicts bulk density model calculated from the porosity and net-to-gross ratio realizations. The fluid
densities are obtained from actual field data (Fig.6). Mineral density and composition for sand and
shale are specified as presented in Fig.6. The density of calcite is taken from literature (Fig.6, Ref.10).
Fig.7 shows a P-wave velocity model generated from the porosity, net-to-gross ratio, and water
saturation realizations. The p-wave velocity of water saturated sand is calculated using empirical
correlation presented in Fig.7 (Han, Ref.10). Gassmann’s relation (Ref.10) was applied for fluid
substitution using bulk modulus obtained from field data and literature value (Fig.7). The P-wave
velocity of shale is calculated using empirical correlation presented in Fig.7 (Gardner, Ref.10). P-
wave velocity of calcite is obtained from the literature (Fig.7, Ref.10). The P-wave impedance model
is computed from bulk density and P-wave velocity and presented in Fig.8. As depicted in Fig.8, shale
layers and calcite bodies are highlighted by high impedance.
3.2. Result of Multiple Seismic Imaging and Automatic Seismic Interpretation

A synthetic seismograph is generated from the rock physics property model and utilized for seismic imaging. Fig.9 depicts the result of multiple seismic imaging obtained by the method of Clapp (Section 2.1). To create a training interpretation result, the horizon and faults are manually picked on an arbitrary selected seismic image (image 1) as shown in Figs.10~11. In this particular example, the boundary between shaly sand/clean sand and that between calcite/clean sand are relatively clear on the seismic image (Fig.10). We decided to pick positive amplitude peaks to create a training structural model (Fig.11).

Fig.12 illustrates the result of automatic seismic interpretation with SIMPAT (Section 2.2) using the manually interpret structural model as a hard training image and also using the seismic image utilized for manual interpretation (image 1) as a soft training image. The left column shows the seismic images used as soft data. The center column depicts the simulated horizons and faults. The right column is the seismic image overlaid by simulated horizons and faults. Shown in the top row is the soft and hard training images used for simulation. As shown in the figure, the result is quite encouraging in this simple preliminary application. However, in some images, horizons are partly missing especially at the zones/ compartments where the response of amplitude is relatively weak.

This missing horizon problem is partly attributed to the similarity calculation method (Manhattan distance) used in SIMPAT algorithm (Ref. 9). The limitation of Manhattan distance is, when applied to ‘sparse’ training images such as edge image, the evaluated similarity of patterns is biased toward ‘sparser’ patterns. This leads to the underestimation of the continuity of image when applied for simulating edge images. Arpat suggested to apply distance transformation to categorical training image in order to avoid this problem (Ref.9). The basic idea is to convert edge images into more blurred images such as proximity maps (Fig.13) and simulate proximity map instead of simulating ‘sparse’ categorical patterns. The example of proximity maps generated from hard training image (i.e. faults and horizons) is depicted in Fig.13. The proximity map is practically an opposite to distance map, thus it is created by calculating the distance to the closest fault or horizon and reversing the normalized distance to proximity measure. The structural model is obtained by back-transforming the simulated proximity maps. Fig.14 shows the result of automatic seismic interpretation through the SIMPAT simulation with distance transformation. As shown in the figure, the reproduction of connectivity of horizons is improved compared to Fig.13.

The other approach for improving automatic seismic interpretation result is to use an E-type estimate for creating structural model, instead of using a single simulated realization. An E-type estimate is obtained from a number of simulated categorical realizations, by calculating the relative...
frequency of occurrence of the categorical variables at each grid node. Therefore, a map of E-type estimate can be considered as a probability map which depicts the local conditional probability of categorical variables. Since automatic seismic interpretation is a pattern conditioning problem rather than a pattern simulation problem, it is a practical idea to build structural model based on the E-type estimate from multiple simulation results, since a map of E-type estimate directly illustrates the likelihood of horizon/fault locations. Fig.15 depicts the E-type estimate of simulated structural image generated from 5 realizations. Distance transformation is not applied for simulation in this case to see the effect of the use of E-type. As shown in the figure, the connectivity of horizons is enhanced compared to Fig.13.

4. Discussion

This paper shows some initial results on creating multiple structural models from multiple seismic data sets. This paper takes the view that often the most important uncertainty lies in the seismic data itself, not in the multiple interpretation on a single seismic image. The method consists of generating multiple seismic data sets by considering the uncertainty in the velocity model and relying on SIMPAT to automatically interpret the results. Many challenges remain as listed below:

1) Test on seismic data set with more variability

The synthetic seismic data set used in this paper is of good quality. As a result, the obtained multiple seismic images are similar to each other. Although the automatic seismic interpretation with SIMPAT showed some encouraging results in this simple and easy problem, it does not guarantee that one would obtain an equally good result if he/she applies the same approach to more difficult problem such that the multiple seismic images show more variation from each other. The method requires more testing using seismic data set with more variability.

2) CPU cost for seismic migration

The CPU time required for the migration of seismic image is also an issue that prevents the multiple seismic imaging from being practical. Especially, migrating 3D seismic data using dozens of different velocity models is almost impossible considering the CPU time required. One of the possible strategies to compromise is to use so called “2.5D model”: That is, migrate the seismic data on selected 2D cross-sections of 3D seismic data, and construct a fence model of reservoir structure. The
final structural model can be obtained by interpolating the horizons and faults between 2D cross-sectional structural interpretations.

3) Automatic gridding of reservoir structure for flow simulation

A reservoir flow simulation model grid is usually built using commercial geo-modeling/gridding software, creating model grids from horizon/fault surfaces. In structurally complex reservoirs, it often requires time-consuming manual job. In order to construct dozens of prior reservoir flow simulation models for history matching from multiple structural interpretation results, an efficient automatic gridding method is desired to reduce the required time and labor.

An approach to automatically construct model grid from the automatic seismic interpretation result is proposed as below:

As shown in the figure, the pixelized structural image generated by SIMPAT is converted into a compartment model, by grouping the pixels enclosed by the same horizons and faults. The reservoir model grid is built by overlaying coarse grids on the boundaries between compartments first, and then subdividing each compartment into fine grids. The example shown in the figure is implemented on 2D structural model. 3D extension of the method, or application for 2.5D structural model, is required.

4) Parameterization of the structural model for automatic history matching

In automatic history matching, the reservoir parameters to be inverted are expressed in the form of vector. The optimization is performed by finding the minimum on N-dimensional Cartesian model space, where N is the dimension of the parameter vector. However, it is difficult to parameterize structural geometry into a limited set of parameters, especially when the structure is complex, since in such reservoirs structural geometry is characterized by the topology of horizons and faults rather than grid data values such as depth of horizon. The history matching approach proposed in this paper (Section 1) starts from multiple prior structural models defined by the uncertainty in seismic imaging, and aims at reducing that uncertainty through the incorporation of production data. Since the structural
models do not fit to the vector-form model space, a new approach for automatic history matching is needed.

In the area of computer science, images are often stored in tree data structure in accordance with similarity distance between images, and tree search algorithm is utilized to find images similar to a given image in a large collection of images (Ref.11). Several tree structures have been proposed to maximize the search efficiency. We propose to apply this technique for automatic history matching problem to find structural models which reproduce historical production data. This idea relies on the assumption that the similarity of structural geometry between reservoir models is strongly related to the similarity of production behavior between them. Thus the validity of this assumption should be carefully tested before implementing the tree-search history matching.

5) Incorporation of probabilistic approach into history matching

One thing to be avoided in the history matching is to select only one structural model which matches best to the production data, and ignore all other structural models at the stage of future performance prediction / development planning. Such an application completely ignores structural uncertainty and waste all of the effort made for modeling the uncertainty in seismic image. Therefore, the automatic history matching method should be designed such that methodology evaluates the posterior probability of structural models through the incorporation of production data. In other words, we should adopt a probabilistic approach to history matching instead of ‘greedy’ optimization technique. The tree structure used for automatic history matching should be designed to fit to this need.

5. References

7. Biondo L. Biondi, 3-D Seismic Imaging, Lecture Note, 2005
8. Jon Claerbout and Sergey Fomel, Image estimation by example: Geophysical soundings
   image construction: multidimensional autoregression, Lecture Note & Electronic publishing
   (http://sepwww.stanford.edu/sep/prof/index.html), 2004
    Conference, 1995
Fig. 1 Facies model
Fig. 2 Net-to-gross ratio model

Shale / Calcite NTG = 0.00
Shale / Calcite Porosity = 0.001

3400 m
- 3120 m
- 2270 m
850 m

680*340 Blocks, Grid Size: DX = 5 m, DZ = 2.5 m

Fig. 3 Porosity model
Shale/Calcite Permeability = 0.001

3400 m
- 3120 m
- 2270 m
850 m

680*340 Blocks, Grid Size: DX = 5 m, DZ = 2.5 m

Fig. 4 Permeability model

Shale/Calcite Permeability = 0.001
SHALE/CALCITE

\[ J(S_w) = 0.12(S_w - S_{wir})^{-0.5} - 0.12504071 \quad (\phi = 0.25, K = 500 \text{ mD}) \]

\[ H = \frac{31831.6 \cdot J(S_w) \cdot TS \cdot (\phi/K)^{0.5}}{\rho_w - \rho_o} \]

OWC = 2688.5 m (from ECLIPSE DATA)

TS = 22 dynes/cm

\[ \rho_w = 995 \text{ kg/m}^3 \text{ (from ECLIPSE DATA)} \]

\[ \rho_o = 730 \text{ kg/m}^3 \text{ (from ECLIPSE DATA)} \]

SAND

\[ J(S_w) = 0.12(S_w - S_{wir})^{-0.5} - 0.12504071 \quad (\phi = 0.25, K = 500 \text{ mD}) \]

\[ H = \frac{31831.6 \cdot J(S_w) \cdot TS \cdot (\phi/K)^{0.5}}{\rho_w - \rho_o} \]

OWC = 2688.5 m (from ECLIPSE DATA)

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\[ \rho_o = 730 \text{ kg/m}^3 \text{ (from ECLIPSE DATA)} \]

SHALE/CALCITE

\[ S_w = 1.00 \]

Fig.5 Water Saturation model
**BULK DENSITY**

Rho_b = phi*rho_fl + (1-phi)*rho_m
rho_fl = rho_w *Sw + rho_o*(1-Sw)

SAND/SHALE
rho_m=rho_sand*NTG+rho_sh*(1-NTG)

CALCITE rho_m=2.71

Mineral composition for rho_sand & rho_sh (from Stanford V channel sand & mud)

<table>
<thead>
<tr>
<th>CLEAN SAND</th>
<th>density</th>
<th>Comp.</th>
<th>SHALE</th>
<th>density</th>
<th>Comp.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quarts</td>
<td>2.654</td>
<td>0.6</td>
<td>Quarts+Rock frg.</td>
<td>2.642</td>
<td>0.2</td>
</tr>
<tr>
<td>Feldspar</td>
<td>2.630</td>
<td>0.3</td>
<td>Clay minerals</td>
<td>2.500</td>
<td>0.8</td>
</tr>
<tr>
<td>Rock frg.</td>
<td>2.710</td>
<td>0.1</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

rho_w = 995 kg/m3 (from ECLIPSE DATA)
rho_o = 730 kg/m3 (from ECLIPSE DATA)

680*340 Blocks, Grid Size: DX = 5 m, DZ = 2.5 m

Fig.6 Bulk density model
CLCITE SAND

\[ V_p = (5.55 - 6.96\phi - 2.18C) \times 1000. \] (30 MPa, Han, Water saturated rock)

\[ V_s = (3.47 - 4.84\phi - 1.87C) \times 1000. \] (30 MPa, Han, Water saturated rock), \( C = 1 - NTG \)

Fluid Substitution (Gassmann)

\[ K_{fl1} = K_{wat}, \quad K_{fl2} = \text{Russ average of } K_{wat} \text{ and } K_{oil} \]

\[ K_{min} = \text{Russ average of } K_{sand} \text{ and } K_{clay} \]

\( K_{wat} = 2.14 \text{ GPa}, \quad K_{oil} = 0.5 \text{ GPa (from ECLIPSE DATA)} \)

\( K_{sand} = 39 \text{ GPa}, \quad K_{clay} = 25 \text{ GPa (from Han)} \)

SHALE

\[ \rho_b = 1.75(V_p/1000.)^{0.265} \] (Gardner 1974)

\[ V_p = 6640 \text{ m/s} \]

Fig.7 P-wave velocity model
Fig. 8 P-wave impedance model
Fig. 9 Multiple seismic images (1/2)
Fig. 9 Multiple seismic images (2/2)
Image 1: Draft Interpretation

Fig. 10 Preliminary manual seismic interpretation
Fig. 12 SIMPAT automatic interpretation results (1/2)
Fig. 12. SIMPAT automatic interpretation results (2/2)
Proximity maps from Hard TI

Fig. 13  Distance transformation of hard training image
Fig 14 SIMPAT automatic interpretation results with distance transformation (1/2)
Fig. 14  SIMPAT automatic interpretation results with distance transformation (2/2)
Fig. 15 SIMPAT automatic interpretation results using E-type map, w/o distance transformation (1/2)
Fig. 15 SIMPAT automatic interpretation results using E-type map, w/o distance transformation (2/2)