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Appropriate formulation of the objective function for the history matching of seismic attributes

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ABSTRACT

The purpose of history matching is to find one or several reservoir models which can reproduce as best as possible all the available data. The available data are traditionally some production data, but today seismic data are often integrated in the history matching process. The way of measuring the misfit between real data and simulated responses has a significant impact on the optimization process and hence on the final optimal model obtained. The classical formulation of the misfit is the least square one, which was used with success for production data. This formulation was naturally extended for seismic data. However, it yields an objective function term which is difficult to reduce. Indeed, seismic data are different from production data since they are defined by millions of points and are generally very noisy. When matching seismic data, the goal is then to capture the main features. As a result, computing a point to point error is not adapted and the resulting objective function is not representative of the quality expected for the match. We propose in this paper to define a more appropriate formulation. The idea is to use some image analysis tools to define a formulation focusing on the main features of seismic images. More precisely, it is based on image segmentation and on a modified Hausdorff metric. We illustrate the success of this formulation on a simple history matching case.

1. Introduction

History matching is an important task in reservoir engineering. It aims at building reliable reservoir models. A reservoir model is said to be reliable when it reproduces all the available data as well as possible. These data fall into two types: static data, which are invariable in time, and dynamic data, which evolve in time according to fluid movements in the reservoir. Traditionally, dynamic data consist of production data collected at wells. Nowadays, seismic data repeated in time can also be acquired. Stratigraphic joint inversion of such seismic data can provide seismic attributes such as waves velocity and P impedances (Delepine et al., 2010). These data constitute a highly informative spatial information. Moreover, the variations of these attributes in time characterize the fluid and pressure variation in the reservoir. It is of invaluable interest to include this information in the matched model (Hall, 2006; Dadashpour et al., 2008, 2009). Indeed, it provides insights about the fluid behavior over extensive areas of the reservoir and can help identify connected regions.

The workflow used to build a reservoir model is a chain of successive modeling steps. First, a geological model is built and populated with petrophysical properties such as porosity and permeability. Then, this model is upscaled to a reservoir grid used to perform a fluid flow simulation. Simulated production data consist of the responses at the wells over time computed by this simulation. Seismic attribute variations (velocity and acoustic impedances) can be derived from the computed pressure and saturation variations through a petro-elastic modeling. Typically, it involves Gassmann equations (Gassmann, 1951) to model fluid effects and Hertz-Mindlin equations (Mindlin, 1949) to model pressure effects. Outputs of the petro-elastic model are then usually filtered for consistency with the typical seismic bandwidth. The resulting seismic attribute variations are called the simulated seismic attributes. In this paper, the comparison with real data is performed between seismic attributes instead of seismic data in order to avoid the seismic forward modeling which is a difficult and costly step (Gosselin et al., 2003).

The matching of the reservoir model with the available data is performed by an iterative process. The different unknown parameters of the model are modified in order to reduce a functional, called the objective function, which measures the misfit between real data and simulated data. The most classical formulation for the objective function is based on least squares. It proved to be efficient for production data (Oliver and Chen, 2010), in the sense

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that it is a good characterization of the error between simulated and real data. In addition, it can be significantly reduced during the history matching process. To integrate seismic data in the reservoir model, a seismic related term should be included in the objective function. This term is the measure of the misfit between the simulated seismic responses and the reference seismic attributes. In previous work, the least square formulation was naturally extended for the evaluation of this misfit. The objective function defined with the least square formulation, denoted by OF_{LS}, is given by

$$OF_{LS} = \frac{1}{2}(d-\tilde{d})^T C^{-1}(d-\tilde{d})$$

where d is the reference data vector, $\tilde{d}$ is the simulated data vector and C is the covariance matrix, which represents the measurement uncertainties (Tarantola, 1987). When the number of seismic data is large, the full covariance matrix is hard to invert. In addition, off diagonals terms are difficult to estimate. Usually, these terms are neglected and the covariance matrix is taken as diagonal.

Different studies show that the minimization of the seismic term is very difficult (Gosselin et al., 2003; Roggero et al., 2007). This is related to the nature of seismic data, which are very different from production data. First, seismic attributes are defined by seismic cubes with millions of pixels, while production data are some curves, given by tens of points. Using a least square formulation for seismic attributes misfit means that the objective function is the sum of pixel by pixel errors. Second, the simulated seismic attributes are derived from a reservoir simulation followed by a petro-elastic modeling step. Due to CPU time issues, reservoir simulation often requires a drastic upscaling, in particular for the horizontal direction. Thus the resolution of the simulated seismic attributes can be very low in comparison to the resolution of the reference ones. This implies that the meaning of the history matching seismic misfit is very different from the meaning of the misfit built for seismic inversion. Third, the seismic attributes to be matched, such as acoustic P impedances for example, are derived from a preliminary inversion process of the seismic data which are generally noisy. In addition, the result of the inversion process is largely dependent on the choice of the prior model, and thus is uncertain. Considering these three points, trying to match precisely each pixel value, as in the least square formulation, seems to be non realistic. Moreover, since the number of parameters for optimization is restricted, we argue that the aim of the history matching of seismic attributes is not to retrieve precisely each pixel value, but rather to capture the main features. As underlined before, the valuable information given by seismic data is a spatial information, like presence of channels or steam chamber growth. Considering this purpose for the history matching of seismic data, it is clear that a formulation which considers each pixel error is not adapted.

This issue was already studied. Gosselin et al. (2003) put in evidence that the traditional diagonal least square formulation was not adapted to seismic data. As already mentioned, correlations between data are neglected for sake of simplicity. When data are the different pixels of a seismic image, this assumption is clearly not valid. The authors propose a correlation function based on an exponential formulation which enables a simple and efficient inversion of the correlation matrix. This approach clearly is an improvement, but it still uses a least square formulation and hence, a point to point misfit computation. On real cases, the convergence of the optimization process remains very difficult, despite the improvement of the formulation. An interesting work was developed by Wu et al. (2004). After noticing that a point to point error is not appropriate to characterize the intuitive similarity that can be observed between two images, the authors propose to use a cross correlation tool. To improve the cross correlation, which can be very low even if two images are visually correlated, they preliminarily perform a statistical analysis of the data (canonical analysis or principal component analysis). They obtain statistical attributes on which they compute the cross correlation. The main advantage of this approach is that PCA makes it possible to compute the correlation between two different types of data (between a saturation map and a seismic map for example). In the history matching process considered here, the misfit is computed between the same type of data. Thus, the PCA is equivalent to a moving average filter. More recently, Jin et al. (2011) proposed to convert seismic images into binary images and then consider a pixel to pixel error between these binary images.

Hence, the aim of this work is to reconsider the seismic term in the objective function and to develop a more appropriate formulation. In the first section, we detail the successive steps leading to the new formulation and illustrate them on two examples of seismic images. Then, the proposed formulation is integrated into a history-matching process. We investigate the potential improvement over the least square approach on a synthetic application case.

2. Definition of the appropriate formulation

In what follows, since seismic data provide an image of the reservoir, terms "map" and "image" will often be used to designate seismic data.

We first illustrate with a simple example that the least square formulation is not appropriate for measuring the misfit of seismic attributes (Fig. 1). To do this, we compute the objective function between a reference seismic attribute map and two simulated maps. The seismic attribute considered here is the variation of P impedances. The reference data are extracted from a steam assisted gravity drainage field case. The reference image, denoted by A, shows the growth of the steam chamber (the increase of gas saturation results in P impedance decrease). The first simulated map, B, is the one obtained with the initial model developed for this case (before history matching). The second simulated map, named C, is the result of the same simulation but without injection of steam in the field. The displayed variations are just due to noise. Visually, the first simulated image is much closer to the reference: the steam chamber is reproduced by simulation, even if it has not the same size and shape as the reference one. Note that this simulated image does not have the same resolution as the reference one, due to the upscaling performed for the fluid-flow simulation. Indeed, the seismic grid consists of a regular grid of 50×49 grid cells of size $2\,m \times 1\,m$, while the upscaled reservoir grid only consists of 28×42 grid cells with maximum size $2\,m \times 1\,m$ near the well. Away from the well and approaching the top of the reservoir, the vertical and horizontal resolutions get coarser. On the second image, there is no steam chamber, and yet, the least square formulation of the objective function gives a smaller value (OF_{LS}(A,C)=115.79) than for the first one (OF_{LS}(A,B)=266.20). From a history matching perspective, this means that the second image is considered as a better one with respect to the reference. In such a case, we cannot expect the history matching process to be successful. Since a seismic map contains a lot of information, the basic idea of our formulation is as a first step to extract the most relevant information and focus on it. Then, the following step is to find an appropriate metric to measure the error between the relevant information derived from real seismic attributes and the one derived from the numerical outputs. The alternative formulation proposed in this paper consists of the three following steps:

1. simplify images to extract the relevant information by filtering and clustering,