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Research paper

Binary 4D seismic history matching, a metric study

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ABSTRACT

This paper explores 4D seismic history matching and it specifically focuses on the objective function used during the optimisation with seismic data. The objective function is calculated by using binary maps, where one map is obtained from the observed seismic data and the other is from one realisation of the optimisation algorithm from the simulation model. In order to decide which set of parameters is a relevant update for the simulation model, an efficient way is required to measure how similar these two binary images are, during their evaluation within the objective function. Behind this aspect of quantification of the similarities or dissimilarities lies the metric notion, or the art of measuring distances. Four metrics are proposed with this study, the well-known Hamming distance, two widely used metrics, the Hausdorff distance and Mutual Information and a recent metric, called the Current Measure Metric. These metrics will be tested and compared on different case scenarios, designed in accordance to a real field case (gas exsolution) before being used in the second part of the paper. Despite its simplicity, the Hamming distance gives positive results, but the Current Measure Metric appears to be a more efficient choice to cover a wider range of scenarios, these conclusions remain true when tested on synthetic and real dataset in a history matching exercise. Some practical aspects of binary map processes will be examined through the paper, as it is shown that it is more proper to use a derivative free optimisation algorithm and a proper metric should be more inclined to capture global features than local features.

1. Introduction

In reservoir engineering, history matching (HM) is an important and necessary process to update the reservoir model and obtain accurate predictions that enhance field management planning (Schulze-Riegert and Ghedan, 2007). This goal is achieved through well history matching (WHM), which is considered a reliable piece of information to update the simulation model. During the past few years, the combination with seismic data called seismic history matching (SHM) is also now an active research area. The challenge with SHM (Fig. 1) is the incorporation of 4D seismic data into the reservoir simulation model (Landa and Horne, 1997). This can be achieved using different seismic attributes as described in Stephen and MacBeth (2006). There are three main ways to proceed, directly in the seismic trace domain (Landrø, 2001), the impedance domain (Ayzenberg et al., 2013), or the pressure-saturation model domain (Falcone et al., 2004). All methods are challenging owing to their complexity and computational time. Ways to circumvent these drawbacks have been explored by Landa and Horne (1997), and more recently by Tillier et al. (2013) and Obidegwu et al. (2015). The latter paper proposes that the simulation and seismic gas maps be converted to binary images so that the history match may use a binary objective function.

With the binary map SHM, an important question is the effect of different thresholds on the search space. A prior understanding of the influence of the threshold could help to enhance this methodology. An additional question is whether there are optimisation methods best suited to search this particular space, or whether the search space is simpler to explore for binary maps. The binary objective function defines the precision of the history matching process, so the threshold should be considered with care. Also important is what information is lost when a threshold is applied, and whether an increase of the number of threshold is beneficial. Another important issue is the technique in measuring the similarity/dissimilarity between two images. For this latter aspect, here it is proposed to analyse different metrics in order to evaluate the binary image matching. For the observed seismic datasets, different situations are considered: gas expansion, dissolution and displacement, therefore a suitable metric must have the capacity to evaluate differences in the images created by these processes. With this aim, here some well-known metrics will be compared to the Current Measure Metric (CMM) (Glaunès et al., 2008; Chesseboeuf et al., 2015) for first a synthetic and then a real

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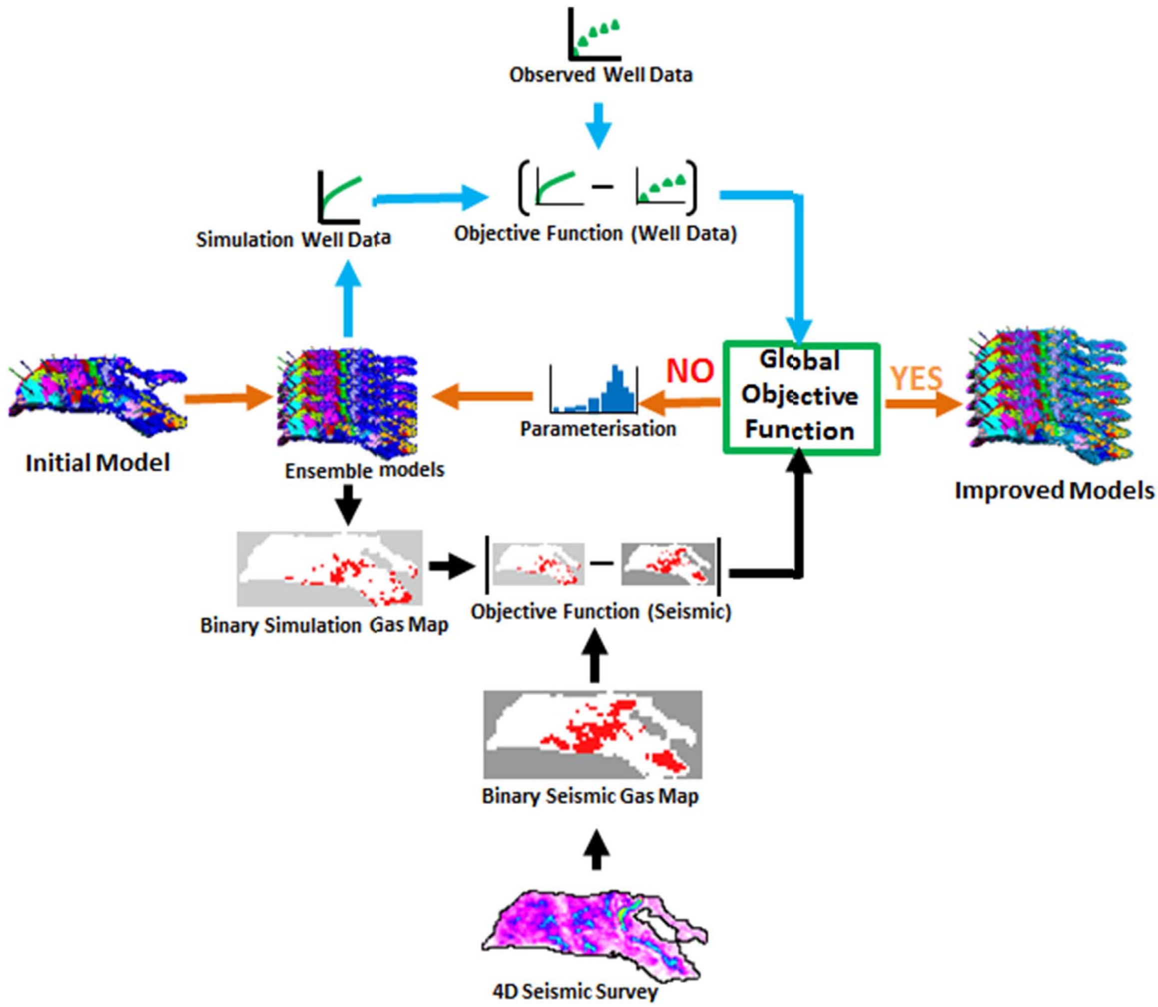

Fig. 1. Workflow of the (4D seismic+well) history matching process used.

field dataset. The CMM is specifically adapted to binary images, and has been successfully used previously in the medical imaging domain.

2. An appropriate thresholding

2.1. The setting up of idealised models

In this part, the aim is to mimic an SHM by a process with reduced computational time and data processing, as compared to working with real data. This also simplifies the analysis of the binary optimisation step. This exercise tests (see part 2.3) the behaviour of the clustering method for the case of gas exsolution. To achieve this end, four idealised models are established that have been designed to capture the main characteristics of the gas distributions and four images are chosen to be used as the observed seismic images. In order to mimic the gas map representation the idealised models are defined by the summation of a number of Gaussian functions. These are based on several map extractions from the real data (discussed later in this paper) and characterise the main patterns generated in a history matching procedure. Four distinctly different models are classified (see Fig. 2). Model 1 has a single centred image

$$\boldsymbol{F}_1 = \boldsymbol{e}^{(-\boldsymbol{a}x^2 - \boldsymbol{b}y^2 + \boldsymbol{E})} \tag{1}$$

where x and y are the spatial variables defined on $x, y=[-2,2]$, $\boldsymbol{a}$ and $\boldsymbol{b}$ represent the parameters to be varied in the SHM, and $\boldsymbol{E}$ stands for the spatially variant amplitude perturbation (see below). For our study, the best fit parameters from our seismic images are $\boldsymbol{a} = \boldsymbol{a}_0 = 0.99$ and $\boldsymbol{b} = \boldsymbol{b}_0 = 1.85$. A perturbation is added to this seismic image generated by e^E, and this avoids the optimisation algorithm obtaining a perfect match to the function in (1) with $E=0$ during the history matching process. e^E does not define a simple translation or rotation, but a functional modification of the Gaussian function. For our work $\boldsymbol{E} = 0.8\boldsymbol{xy}$, and Model 1 is defined as in Eq. (1). For Model 2 we add a second off-centre Gaussian, whilst models 3 and 4 show further increasing complexity (see Appendix). Different thresholds are then applied to the maps generated by the different idealised seismic images and their corresponding models (Fig. 2); a k-means algorithm is used for this step. And then a genetic algorithm is used as the optimisation procedure to history match these images.

2.2. Clustering

The observed seismic attributes contain a lot of information about the field, but in the context of the binary map the intention is to extract just the right amount of useful information. Thus the objective is to simplify the map keeping only the main features (Tillier et al., 2013). In this case, the main feature is exsolved gas which can be characterised by low values of seismic impedance (Calvert et al., 2014). The binary map is a reduction of the level of