



Image processing tools for better incorporation of 4D seismic data into reservoir models

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ABSTRACT

Reservoir engineers have to predict the behavior of a hydrocarbon reservoir by building a simulation model which can best reproduce the data collected in the field. These data fall into two types: static data, which are invariable in time, and dynamic data, which evolve according to fluid motions in the reservoir. In this paper, we focus on the integration of dynamic data related to four-dimensional (4D) inverted seismic data. Such seismic data constitute an invaluable source of information on fluid displacement and geology over extensive areas of the reservoir. However, incorporating them in the reservoir model through a matching process is a challenging task. Classical formulations of the objective function, which computes the misfit between observed data and responses computed by the reservoir model, are not adapted to 4D inverted seismic data. For example, a least square based mismatch is not representative of the visual difference between two seismic images. In this paper, we define a new formulation of the objective function based on simplification of seismic data in order to extract relevant information. This simplification involves filtering and segmentation techniques, as well as image comparison methods rooted in image analysis. More precisely, we focus on the non-local means algorithm for filtering, on the level-set framework for segmentation and on the local modified Hausdorff distance for image comparison. We investigate the efficiency of such techniques in the context of seismic data, and illustrate their potential on a synthetic history matching reservoir example.

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1. Introduction

In the context of reservoir engineering, the goal of history matching is to build a reliable reservoir model which can reproduce the field-observed data. These data fall into two types: static data, which are invariable in time, and dynamic data, which evolve in time according to fluid motion in the reservoir. Traditionally, dynamic data consist of production data collected at wells. Nowadays, another type of data, called time-lapse seismic data, can be acquired. These data are generated by using vibrations to capture a two-dimensional (2D) picture of rock layers beneath the surface at the same localization but at different times. These data constitute highly informative spatial information. Geologists interpret these data to make an estimated picture which can reveal the hydrocarbon motion under the surface without drilling.

Incorporating such data in a reservoir model calls for a specific workflow, which consists of a chain of successive modeling steps. First, a geological model is built and fed with petro-physical properties such as porosity and permeability. Then this

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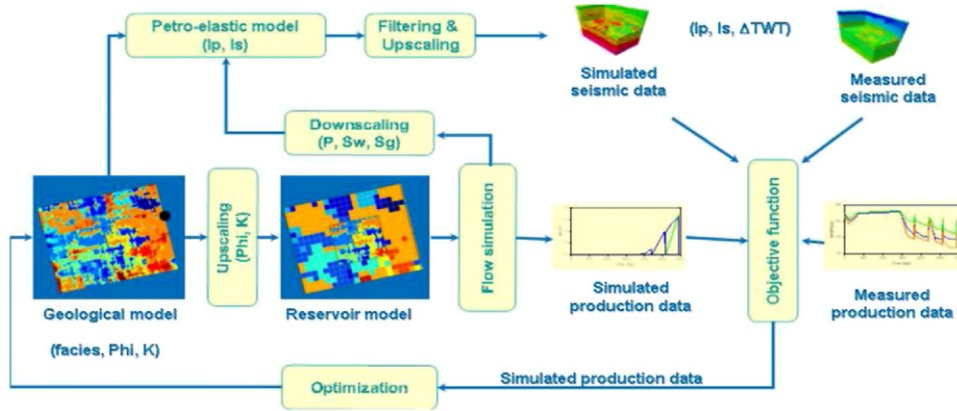


Fig. 1. Illustration of the history matching loop.

model is upscaled to a reservoir grid used to perform a fluid flow simulation [1]. The result of these equations provides some simulated production data. Seismic attribute variations (velocity and acoustic impedances) can be derived from the computed pressure and saturation variations through a petro-elastic modeling. Typically, this involves linear equations: the Gassmann equations [2] to model fluid effects and the Hertz–Mindlin equations [3] 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. Finally, a comparison between simulated and observed data is performed through the evaluation of a so-called objective function. This objective function measures the misfit between available data and data simulated by a given reservoir model. Fig. 1 summarizes the workflow used to build a reservoir model.

The history matching process is thus an inverse problem in which an optimization method is used to adjust the unknown parameters in order to reduce the value of the objective function. If the formulation of the objective function is adapted, at the end of the process the simulated data produced by the matched model will be close to the available data. Consequently, the definition of the objective function is crucial for this workflow. Currently, the objective function is based on a least square formulation, denoted by OF_{LS} , and given by

$$OF_{LS} = \frac{1}{2}(d - d^s)^t C^{-1}(d - d^s),$$

where d is the reference data vector, d^s is the simulated data vector and C is the covariance matrix, which represents the measurement uncertainties. This formulation encompasses both production and seismic data: as a result, all data are treated in the same way. This formulation proved to be efficient for production data, in the sense that it is a good characterization of the error between simulated and real data. Moreover, during the history matching process, the objective function can be reduced significantly. However, this formulation is not suitable for seismic data. Indeed, the nature of inverted seismic data is totally different from that of production data. First, production data are few and are represented by curves, whereas seismic data are made of millions of points in a 3D cube with spatial information. Second, while the production data collected on the field are only corrupted by measurement errors, the available seismic attributes, such as acoustic P impedances, have two types of uncertainty. Besides measurement errors observed during the seismic survey, additional uncertainty comes from the inversion process, which transforms seismic reflection data into a quantitative rock property describing the reservoir. Therefore, seismic data are more uncertain than production data: it is pointless to try to match each cell of a seismic impedance cube exactly as is done with a least square comparison. Let us illustrate this fact with a simple example. In Fig. 2, we display three seismic maps corresponding to a steam injection scenario in a heavy oil reservoir. The map on the left is the reference data to be matched, and it shows the growth of a steam chamber. The first simulated map displayed in Fig. 2, middle, is the one obtained with an initial model before history matching. The last image on the right corresponds to a scenario without steam injection. Visually, the initial model is much closer to the reference data than the model without injection. Indeed, in this case the steam chamber is reproduced by simulation. However, the value of the objective function computed with the least square formulation between the reference data and the data produced by the initial model is higher (about 341) than the discrepancy calculated between the reference and the same model without injection (about 120). This example clearly illustrates that the formulation with the least square method does not characterize the error between two set of seismic inverted data.

Recently, Tillier et al. [4] proposed replacing the least square formulation with a new measure based on image analysis tools. First, reference and simulated seismic data are filtered and clustered in order to extract the relevant information from the images. Then these simplified images are compared using a modified local Hausdorff distance in order to capture spatial differences. Finally, the total error is computed as the L^2 norm of the Hausdorff distances. They show that this procedure yields a discrepancy measure which is able to discriminate seismic maps very efficiently on several reservoir cases [4,5].

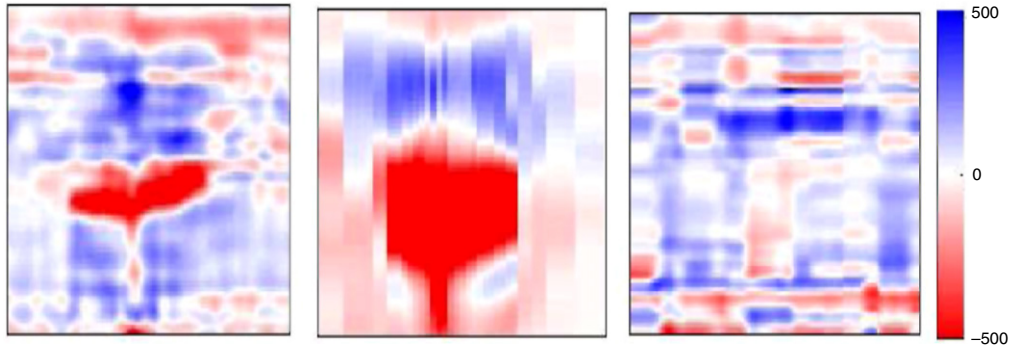


Fig. 2. Least square formulation for seismic data. Reference (left), simulated (middle) and non-informative map (right). The value of the objective function between the reference and the simulation is 341, while it is about 120 between the reference and the non-informative map.

However, this new formulation consists of very elementary tools. The filtering step calls for a simple median filter, while the classification step is performed with the k -means algorithm, which does not account for spatial correlations in the image.

In this paper, we go one step further by proposing state-of-the-art methods for both the filtering and clustering steps. On the one hand, we investigate the potential of the non-local (NL) means filter, which was shown to perform very well on several examples [6]. Its efficiency still has to be studied in the context of seismic data. On the other hand, we focus on segmentation methods based on active contours without edges [7] in order to replace the k -means algorithm. Since segmentation methods use spatial information to detect shapes inside an image, they are expected to behave better than simple clustering. In the context of 4D seismic maps, we will generally extract two or three regions of interest. As a result, we extend the modified local Hausdorff distance to deal with more than two levels, in order to compare images with three target areas. The paper is organized as follows. In Section 2, we first describe the new objective function and study the impact of the new NL means filtering and segmentation steps on the procedure. Section 3 is dedicated to a synthetic reservoir case. We illustrate the potential of this new formulation with respect to the least square approach.

2. Objective function adapted to 4D seismic data: simplification and dissimilarities of images

Since a seismic map contains a lot of information, we propose first to extract the most relevant information and focus on it. Then the following step is to use an appropriate metric to measure the error between the relevant information derived from real seismic attributes and that derived from the numerical outputs. The proposed formulation then consists of the three following steps.

1. Simplifying images to extract the relevant information by filtering and segmenting. This process will be applied on both observed and simulated 4D seismic images.
2. Measuring a local dissimilarity between the two simplified images.
3. Defining a global dissimilarity to include it into the objective function.

In what follows, we will first study the NL means filter [6] and a variational segmentation technique [8]. These tools will provide an efficient simplification step. Then we adapt the local modified Hausdorff distance which was already proposed for step 2 in [4]. In order to account for more than two regions of interest, we use the distance transform for real values proposed in [9]. Finally, step 3 will only consist in computing the L^2 -norm of the local Hausdorff distances, and will not be detailed here.

2.1. Simplification of seismic attributes with filtering and image segmentation

2.1.1. Preliminary step: smoothing images

As mentioned in Section 1, inverted seismic attributes are noisy and are also tainted with uncertainty due to the inversion process. Moreover, simulated seismic maps can also exhibit small patterns which are somewhat irrelevant and difficult to interpret. In order to prepare the segmentation step, we thus propose cleaning up the data by filtering them.

The aim of filtering methods is to find the best estimation of an original image from its noisy version. A filtering method is based on the following decomposition:

$$u = D_h(u) + n(D_h, u), \quad (1)$$

where u is the noisy image, $D_h(u)$ is the estimated image, $n(D_h, u)$ is the estimated noise affecting the data and h is a filtering parameter. Among the several available local methods, some are based on local smoothing filters (arithmetic average filter, Gaussian filter, median filter or a filter based on calculus of variations [10]). For example, the arithmetic average filter replaces the value of one pixel by the arithmetic average of its neighboring pixels, the size of the research window being

related to the parameter of the filter. Although computationally efficient, this filter is known to have serious difficulties in preserving the contours: it is a low-pass filter. The use of the median filter, which replaces the value of each pixel by the median value of its neighboring pixels, makes it possible to lessen this effect. However, a large amount of noise cannot be removed by the median filter. Local filters generally share this drawback.

Other filters worth mentioning call for thresholding techniques (Wiener–Fourier filter, Yaroslavsky local adaptative filters based on discrete cosine transform [11] or the wavelet thresholding method [12]). Recently, Buades et al. [6] introduced an efficient smoothing method known as the non-local means filter (NL means filter). The main idea, first used in [13] for texture synthesis, is to take advantage of self-similarities in images by comparing local neighborhoods across the whole image. In the case of 4D inverted seismic images, this approach seems to be promising: seismic images are not structured as natural pictures and consist of geological patterns or fluid displacements over large areas of the image. Coming back to Eq. (1), the NL means estimate of the denoised image is given by

$$D_h(u) = \frac{\sum_{y \in I} \exp \left\{ -\frac{\|U(x) - U(y)\|^2}{h^2} \right\} u(y)}{\sum_{y \in I} \exp \left\{ -\frac{\|U(x) - U(y)\|^2}{h^2} \right\}}, \quad (2)$$

where $U(x)$ and $U(y)$ are the neighborhood windows, or patches, with respectively x and y as the central pixel. The distance between two patches is

$$\|U(x) - U(y)\| = \frac{1}{s} \sum_{|j| \leq \frac{s-1}{2}} |u(x+j) - u(y+j)|, \quad (3)$$

where s is the patch size. In practice, the filtering parameter h depends on the image noise variance. This variance is unknown for a real picture u , but a possible estimation is given by the empirical variance

$$\sigma^2(u) = \frac{1}{|I|} \sum_{x \in I} (u(x) - \bar{u})^2,$$

where I is the set of all pixels of u , $|I|$ is the total number of pixels and $\bar{u} = \frac{1}{|I|} \sum_{x \in I} u(i)$.

In order to investigate the behavior of the NL means filter on seismic images, we propose comparing it with the arithmetic average and the median filter, which were already studied in this setting in [5]. In both examples we set the filtering parameter h to 0.03 and the size of the patch to 7.

The first illustrative example deals with the steam chamber reservoir model presented in Section 1. The noisy image is depicted in Fig. 3, top left. Results obtained with the three filters are given in the top row. As expected, the moving average filter exhibits oversmoothing, hence producing a blurred image, while the median filter makes it possible to preserve the steam chamber contours. The NL means filter (Fig. 3-row 1, column 4) also keeps the contours intact. In addition, we provide in Fig. 3, bottom row, the removed noise for each filter, i.e., the difference between the noisy image and its denoised version. The image structure can be observed in the noise removed by the arithmetic average filter, which explains why a lot of information is lost in this case. In contrast, the median filter removes a very small amount of noise: structural information is preserved, but small irrelevant patterns are not cut off. Between these two unwanted behaviors, the NL means filter produces a very clean image, in which almost all the noise has been removed while preserving the steam chamber.

The second example focuses on a reservoir model encompassing several channels, i.e., geological structures which are preferential ways for fluid-flow displacement. Here, objects are numerous and the contours have to be identified correctly since connectivity between channels is crucial for fluid displacements. In the top left part of Fig. 4, the reference image consists of a noisy version of a synthetic seismic image. The initial map, containing normalized values between 0 and 1, has been corrupted by a Gaussian noise with standard deviation equal to 0.03. Red areas correspond to channels with gas displacement and blue areas to channels with water displacement. Once again, the arithmetic average filter oversmooths the channel objects, and a lot of structural and connectivity information is lost, as can be seen in the removed noise. Channels are less blurred with the median filter, but many details are removed in the red diagonal part of the image. Finally, the noise removed by the NL means filter looks like a white noise and the channel structure is very well preserved.

These reservoir examples clearly illustrate the large improvement provided by the NL means filter in the seismic data framework. This is the reason why we propose including it into our objective function formulation. From a computational perspective, let us mention that Buades et al. advise computing the weighted sum in Eq. (2) only on a subset of the image called the search window, in order to reduce the CPU time. However, since relevant information (geological structures, fluid displacements) is observed on extensive areas of the image, we suggest making this computation on the full image.

2.2. Segmentation

Seismic maps usually contain a lot of information. As mentioned before, in order to match the simulated map with the real data, we want to simplify both of them to only keep the main features. Consequently, the amount of data will be significantly reduced in order to compare only relevant information.

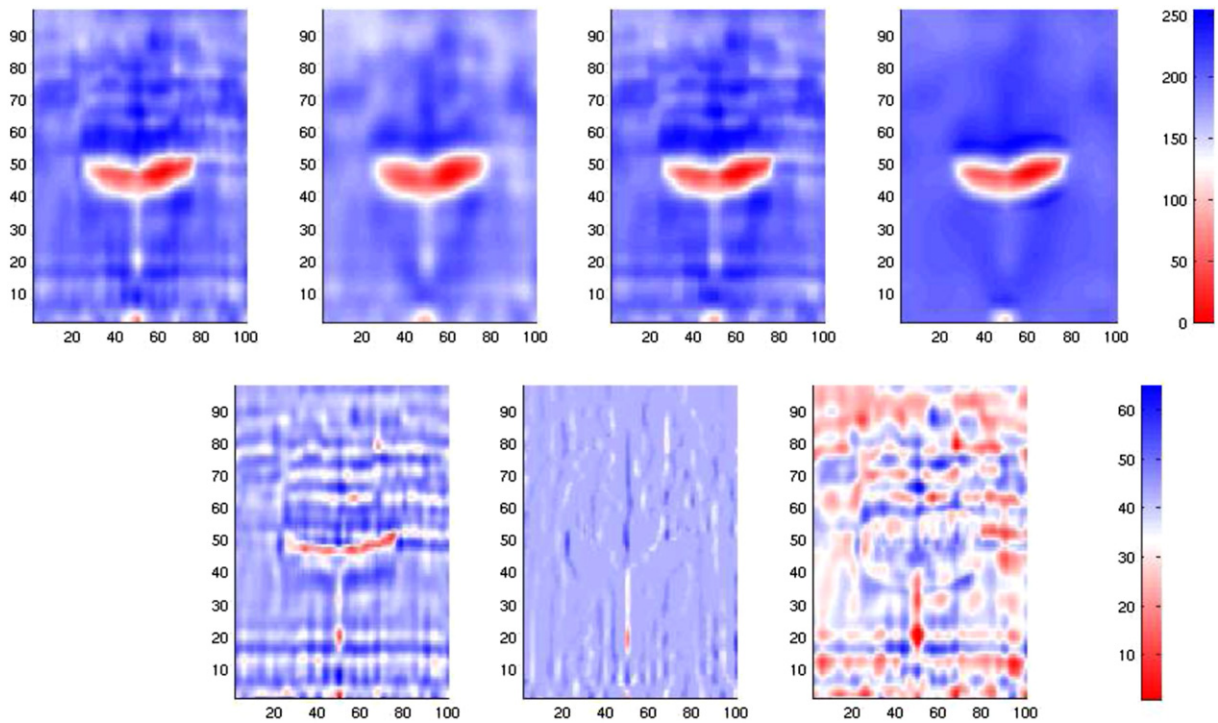


Fig. 3. Comparison of three filters on a steam chamber reservoir case. First row: reference and filtered maps. Second row: noise removal. From left to right: reference, arithmetic average filter, median filter and NL means filter.

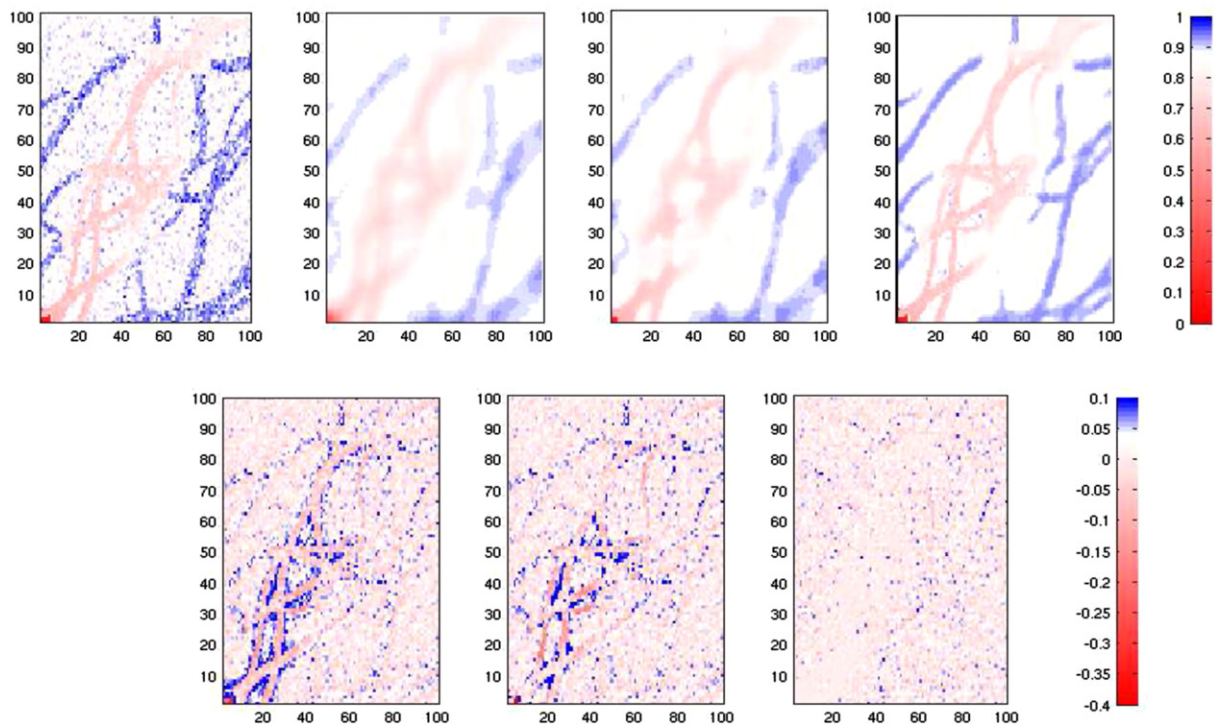


Fig. 4. Comparison of three filters on a channelized reservoir case. First row: reference and filtered maps. Second row: noise removal. From left to right: reference, arithmetic average filter, median filter and NL means filter.

This step has to be done automatically without the operation of the user. Indeed, the history matching process usually involves hundreds of calls to the objective function during the iterations of the optimization algorithm. Previously, in [4],

statistical clustering methods such as the k -means algorithm have been tested for simplification of the data. However, the proposed methods only deal with the absolute value of seismic attributes and do not incorporate information on structures and objects. Here, we propose improving this clustering step by applying a segmentation based on variational methods, which accounts for spatial correlations in the image.

In the image processing community, segmentation is the decomposition of an image into different areas of interest. For example, the watershed transform [14] is a basic tool of mathematical morphology for image segmentation. It is based on an analogy with topographic relief by comparing images to relief maps, and where contours are defined as the water meeting points in a scenario of flood of the relief. This method uses the gradient of the image and cannot be relevant when the edges in images are not well-defined. Deformable models consist of algorithms which generate curves that move within images to delineate object boundaries by minimizing an energy functional. Among the existing methods, geodesic active contours [15,16] and level set methods developed in [17] are the reference ones. Generally, they use an edge detector based on the gradient of the image.

In our case, even after applying a denoising method, the edges of the objects contained in the seismic map are not accurate. As a result, gradient-based methods are not well-suited for seismic maps. The active contours without edges proposed in [8,18,7] makes it possible to circumvent this limitation. This model uses a stopping term based on Mumford–Shah segmentation technique, and it has several advantages. First, it detects edges with and without gradient, and second, the initial curve does not necessarily need to be initialized around the objects to be detected. Then it gives a partition of the image into two regions, the first region formed by the set of the detected objects and the second one consisting of the background. In our case, the objects to be detected can be for instance channels, steam chambers or any fluid displacement identified in the reservoir.

For illustration purposes, we first recall the reduced case introduced in [19]. Given a function u_0 , which in the context of image segmentation is the image to be segmented, we are looking for its optimal piecewise-constant decomposition. This problem is called the minimal partition problem. Mumford and Shah [19] propose solving it by minimizing the following functional:

$$F^{MS}(K, u) = \sum_i \int_{\Omega_i} |u_0 - c_i|^2 dx + \mu \int_K d\mathcal{H}^1, \quad (4)$$

where $K = \cup_i \partial\Omega_i$ is a set of boundaries, $u = c_i$ inside each component Ω_i of $\Omega \setminus K$ and $\mathcal{H}^1$ is the one-dimensional Hausdorff measure. In two dimensions, $\mathcal{H}^1$ is the length of the boundaries K . Generalization to three dimensions involves $\mathcal{H}^2$, the surface area of K . This energy is minimized with respect to the variable c_i by setting it to the mean of the image over Ω_i , i.e., $c_i = \frac{\int_{\Omega_i} u_0}{|\Omega_i|} dx$, where Ω_i represents a region where u is constant, and $\partial\Omega_i$ is the boundary of this region.

The variational approach proposed in [20] can be applied to Mumford–Shah minimization problem. The unknown boundaries $\partial\Omega$ are represented by the zero level set of a Lipschitz continuous function. Such a function $\phi : \Omega \rightarrow \mathbb{R}$ is used to divide the domain Ω into two open regions, defined respectively by $\{x \in \Omega, \phi(x) < 0\}$ and $\{x \in \Omega, \phi(x) > 0\}$. The edges of the objects to be identified in the image are then defined by $\{x \in \Omega, \phi(x) = 0\}$. Finally, the energy can be minimized under the following constraint:

$$u(x) = c_1 H(\phi(x)) + c_2 H(-\phi(x)),$$

where H denotes the one-dimensional Heaviside function. Based on the Mumford–Shah equation, Chan and Vese [8] proposed a new model for active contours involving minimization of the following energy:

$$F(c_1, c_2, \mathcal{C}) = \lambda_1 \int_{\text{inside}(\mathcal{C})} (u_0(x, y) - c_1)^2 dx dy + \lambda_2 \int_{\text{outside}(\mathcal{C})} (u_0(x, y) - c_2)^2 dx dy + \mu \text{Length}(\mathcal{C}) + \nu \text{Area}(\mathcal{C}), \quad (5)$$

where $\mathcal{C}$ is an evolving curve in Ω , $\mu > 0$ and $\nu > 0$ are regularization parameters and λ_1 and λ_2 are the weights assigned to each region.

Let us illustrate this model on the steam chamber example, where the object to be identified is precisely the steam chamber appearing in the middle of the image. Note first that the pixel values have to be non-negative in order to avoid cancellations in the average inside our target regions (steam chamber and the background) for c_1 and c_2 . Consequently, original seismic attributes are linearly mapped to grey-level pixels between 0 and 255. In Fig. 5, left, we recall the image obtained after NL means filtering. The result obtained after segmentation is given in Fig. 5, right. Here, the steam chamber is clearly identified and separated from the non-informative background. Note also that the injection point at the bottom of the image is extracted.

In this case, segmentation performs very well and makes it possible to extract the relevant information, i.e., the steam chamber growth. However, in general, 4D seismic images exhibit three types of impedance variation:

- regions with negative variations, which correspond to gas saturation or pressure increase (e.g., steam chamber in previous example);
- regions with positive variations, involving pressure decrease or water saturation increase;
- regions with almost zero variation, where there is no fluid displacement.

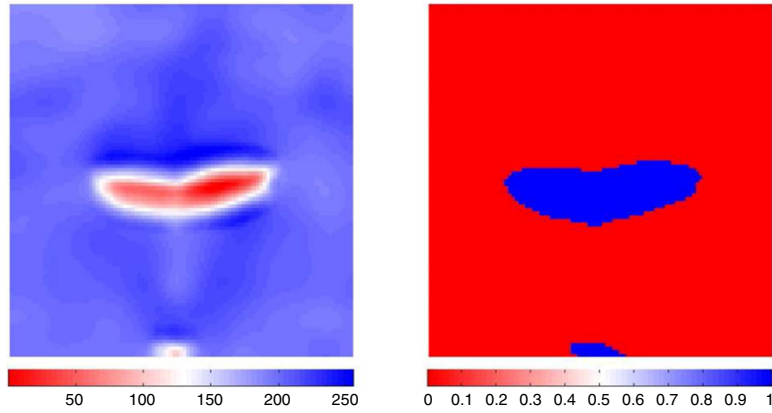


Fig. 5. Chan and Vese segmentation on the steam chamber reservoir case. Left: Seismic map after NL means filtering. Right: Segmentation result (0: background, 1: detected object) with $\lambda_1 = 1$, $\lambda_2 = 4$, $\mu = 4500$, $\nu = 0$.

Direct application of the previous segmentation methodology will then fail to retrieve these three types of relevant region. In order to represent more than two regions, a multiphase level-set framework was introduced in [18], where several functions ϕ_i are used. Another generalization was proposed in [7], where they use the idea of multilayer techniques for modeling epitaxial growth from [21] in order to represent several regions with fewer level-set functions. Here, we focus on this method and consider only one level-set function with an additional level. This model, which now divides the image into three regions $R_1 = \{x : \phi(x) < 0\}$, $R_2 = \{x : 0 < \phi(x) < l\}$ and $R_3 = \{x : \phi(x) > l\}$, hinges upon the minimization of the following energy:

$$F(c_1, c_2, c_3, \phi) = \int_{\Omega} |u_0(x) - c_1|^2 H(-\phi(x)) dx + \int_{\Omega} |u_0(x) - c_2|^2 H(\phi(x)) H(l - \phi) dx \\ + \int_{\Omega} |u_0(x) - c_3|^2 H(\phi(x) - l) dx + \mu \left[\int_{\Omega} |\nabla H(\phi)| dx + \int_{\Omega} |\nabla H(\phi(x) - l)| dx \right], \quad (6)$$

where c_1, c_2 and c_3 are the means over each region and $\mu > 0$ is a regularization parameter. $\int_{\Omega} |\nabla H(\phi)| dx$ and $\int_{\Omega} |\nabla H(\phi(x) - l)| dx$ represent the length of the boundary between R_1, R_2 and R_2, R_3 , respectively. The segmented image is finally given by

$$u(x) = c_1 H(-\phi(x)) + c_2 H(\phi(x)) H(l - \phi(x)) + c_3 H(\phi(x) - l).$$

In order to write the associated Euler–Lagrange equation and to minimize this energy with respect to the level-set function ϕ , the Heaviside function is approximated with a regularized version $H_{\varepsilon} \in C^1$. According to [8], we retain the following regularization of H :

$$H_{\varepsilon}(x) = \frac{1}{2} \left(1 + \frac{1}{\pi} \operatorname{atan} \left(\frac{x}{\varepsilon} \right) \right),$$

and its derivative is given by

$$\delta_{\varepsilon}(x) = H'_{\varepsilon} = \frac{1}{\pi} \frac{\varepsilon}{\varepsilon^2 + x^2}.$$

Minimizing the regularized energy with respect to ϕ , c_1 , c_2 and c_3 yields the associated Euler–Lagrange equations, where the descent direction is parameterized by an artificial time $t \geq 0$:

$$\begin{aligned} \phi(0, x) &= \phi_0(x), \\ c_1(t) &= \frac{\int_{\Omega} u_0(x) H_{\varepsilon}(-\phi(t, x)) dx}{\int_{\Omega} H_{\varepsilon}(-\phi(t, x)) dx}, \\ c_2(t) &= \frac{\int_{\Omega} u_0(x) H_{\varepsilon}(\phi(t, x)) H(l - \phi(t, x)) dx}{\int_{\Omega} H_{\varepsilon}(\phi(t, x)) H(l - \phi(t, x)) dx}, \\ c_3(t) &= \frac{\int_{\Omega} u_0(x) H_{\varepsilon}(\phi(t, x) - l) dx}{\int_{\Omega} H_{\varepsilon}(\phi(t, x) - l) dx}, \\ \frac{\partial \phi}{\partial t} &= \delta_{\varepsilon}(\phi) \left[|u_0 - c_1|^2 - |u_0 - c_2|^2 H_{\varepsilon}(l - \phi) + \mu \operatorname{div} \left(\frac{\nabla \phi}{|\nabla \phi|} \right) \right] \\ &\quad + \delta_{\varepsilon}(\phi - l) \left[H_{\varepsilon}(\phi) |u_0 - c_2|^2 - |u_0 - c_3|^2 + \mu \operatorname{div} \left(\frac{\nabla \phi}{|\nabla \phi|} \right) \right], \end{aligned}$$

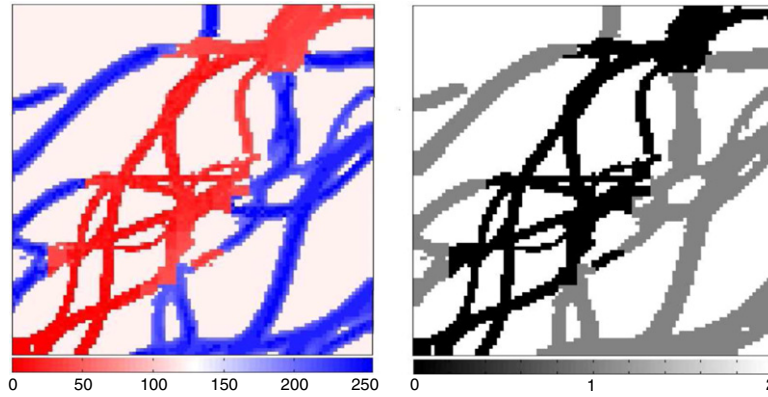


Fig. 6. Multilayer level set segmentation on the channelized reservoir case. Left: Seismic map after NL means filtering and histogram equalization. Right: Segmentation result (0: first detected region, 1: second detected region, 2: background).

$$\frac{(\delta_\varepsilon(\phi) + \delta_\varepsilon(\phi - l))\nabla\phi}{|\nabla\phi|} \cdot \vec{n} = 0 \quad \text{on } \partial\Omega, \quad t > 0. \quad (7)$$

Here, $\vec{n}$ is the unit outward normal to $\partial\Omega$. This energy is not convex (but we can prove the existence of minimizers using characteristic functions); there is no guarantee of finding the optimal minimizer. With this new formulation for segmentation on three regions, we can now investigate its efficiency on the channelized reservoir already presented. In this example, positive variations correspond to gas displacement and negative ones to water movement. As in the steam chamber example, some pretreatment of the data is required for efficient computation of the means over regions. The linear mapping proposed before is no longer suitable, as positive and negative variations do not share the same order of magnitude. Here, a fair balance between positive and negative regions is achieved through histogram equalization [22]: original data are transformed so as to be distributed as close as possible to the uniform distribution on $[0, 255]$. The seismic image after NL means filtering and histogram equalization is given in Fig. 6, left. The corresponding image after three-class segmentation is depicted in Fig. 6, right. The regions identified by segmentation perfectly correspond to the expected areas, meaning that all fluid displacements are correctly extracted from the original seismic map.

2.3. Image comparison and computation of the objective function

In the context of history matching, the previous segmentation step yields two segmented images in two or three regions: one for the reference 4D inverted seismic image and one for the image simulated by the reservoir model. Now, the goal is to establish the differences between these two simplified images and compute an objective function characterizing their mismatch. In a previous work [4], a computation of a local dissimilarity map (LDM) has been efficiently used to compare two binary images. Here, we extend this formulation to three classes. In this section, we first recall the main ingredients to compute the LDM between two binary images. Then we extend this method to compute the difference between images encompassing three classes. A global dissimilarity index is finally computed to obtain the value of the objective function between two images.

2.3.1. Local dissimilarity map

The Hausdorff distance is known to be an efficient tool for image matching [23,24] or face recognition [25]. Given two non-empty sets of points $\mathbf{A} = (a_1, \dots, a_n) \in (\mathbb{R}^2)^n$, $\mathbf{B} = (b_1, \dots, b_n) \in (\mathbb{R}^2)^n$ and an underlying distance d , the Hausdorff distance between $\mathbf{A}$ and $\mathbf{B}$ is given by

$$D_H(\mathbf{A}, \mathbf{B}) = \max(h(\mathbf{A}, \mathbf{B}), h(\mathbf{B}, \mathbf{A})),$$

where $h(\mathbf{A}, \mathbf{B}) = \max_{a \in \mathbf{A}} (\min_{b \in \mathbf{B}} d(a, b))$. In image processing applications, this distance can be viewed as a dissimilarity measure between two binary images A and B . The Hausdorff distance has good properties, but is quite sensitive to noise since it accounts for the most distant points in A and B . Several modifications of the Hausdorff distance have been proposed to improve it. The interested reader is referred to Zhao [26] for an overview of these modified distances. However, all of them are global and do not take into account local dissimilarities. To consider such a local aspect, Baudrier et al. [27] introduced the local dissimilarity map (LDM), which compares the two images locally through a sliding window centered on each considered pixel. The authors also propose a criterion to determine, for each pixel, the optimal size of the window. Practically, the LDM has an efficient formulation through the so-called distance transform. The distance transform of a given set associates, to every point, its distance to the nearest point in this set. More precisely, for binary images, the distance transform at one pixel is the distance between this pixel and the nearest black pixel (if the white color is the background and the black color is the information of the binary image). Any metric could be used to measure the distance between two

points, the most classical choice being the Euclidean distance. Using this distance transform, the LDM between two binary images A and B , at a pixel x , is given by

$$LDM_{A,B}(x) = |A(x) - B(x)| \max(dt_A(x), dt_B(x)), \quad (8)$$

where $dt_A(x)$ and $dt_B(x)$ are the distance transforms of image A and B at pixel x , respectively. The definition of the LDM (8) can be directly applied to grey-level images. However, while the definition of the distance transform is unique for binary images, this is no longer the case when dealing with grey-level ones. Extensions of the distance transform for grey images are achieved either through an extended concept of distance between pixels, or with a new background definition. The grey-weighted distance transform and the weighted distance transform on curve space are two examples of such a distance transform extending distances between pixels. Both distances are studied in [28]. Besides, an approach based on an extension of the concept of background is proposed in [29]. Here, we focus on the distance transform for real-valued functions proposed in [9]. The main idea is to consider a grey-level image I defined on $\mathbb{R}^2$ as a binary volume defined on $\mathbb{R}^2 \times \mathbb{R}$. The introduction of this additional dimension leads to the definition of the hypograph of image I given by

$$\text{hypo } I = \{(x, t) \in \mathbb{R}^2, I(x) \geq t\}.$$

This set consists of binary images obtained with all possible thresholds applied to image I . The original distance transform is then computed for each binary image included in $\text{hypo } I$, and the new distance transform is finally given by their weighted sum over the hypograph. For instance, if I encompasses grey-level pixels in $[0, 1]$, the ν -weighted distance transform is defined as follows:

$$\bar{d}(x, I) = \int_{\inf I}^{\sup I} d(x, \mathcal{I}_t) \nu(dt),$$

where ν is a finite measure on $[0, 1]$ and $\mathcal{I}_t = \{x \in \mathbb{R}^2, I \geq t\}$. Similarly, if I is discretized on $[0, 255]$ and has values between a and b , the ν -weighted distance transform becomes

$$\bar{d}(x, I) = \frac{1}{255} \sum_{i=a}^b d(x, \mathcal{I}_i) w_i, \quad (9)$$

for some weights w_i . In both formulations above, d is a distance between a point and a set, classically given by $d(x, F) = \inf\{\rho(x, y), y \in F\}$ for some point x and a set F . Here, ρ is chosen to be the Euclidean distance, but any distance could be used. This new distance transform is then used in Eq. (8) to compute the LDM between the simulated and the reference segmented images.

We illustrate in Fig. 7 this new distance transform on the channelized reservoir case. Here, we consider two different configurations, where the geology is fixed (i.e., position of channels) but the permeability inside the channels varies. In particular, model M1 (top) has a lower permeability than model M2 (bottom), which explains why we can see fluid flow outside the channels in model M2. The LDM between these two models clearly shows the visual differences between them. Indeed, high values of the LDM are located around the channels where the fluid flows are different. Finally, the LDM is summarized in a scalar objective function through the L^2 -norm averaging.

2.4. Summary

Finally, the new formulation adapted to 4D seismic data consists of the following steps.

1. Apply the NL means filter on real seismic attributes and on the ones derived from the responses of the given reservoir model.
2. Extract relevant information from both maps using the following.
 - The Chan and Vese segmentation method [8] for two regions.
 - The Chung and Vese segmentation method [7] for three regions.
 Note that preliminary transformations of the data may be needed before segmentation (linear mapping, histogram equalization).
3. Compute the LDM between the segmented images with the appropriate distance transform (depending on the number of classes).
4. Compute the L^2 norm of the LDM to obtain the final scalar objective function.

3. Application to seismic data and comparison with the standard objective function

In this section, we investigate our formulation on a reservoir case example. We focus on the PUNQ-S3 (Production forecasting with UNCertainty Quantification) model. It is a 3D synthetic reservoir model derived from a real field of the North Sea Brent reservoir operated by Elf Exploration and Production. The PUNQ-S3 model is considered as a benchmark for testing the application of inversion and optimization methods. The details of the model are provided at the Norwegian Computing Centre PUNQ Complex Model website [30]. The reservoir is surrounded by an aquifer in the north and the west,

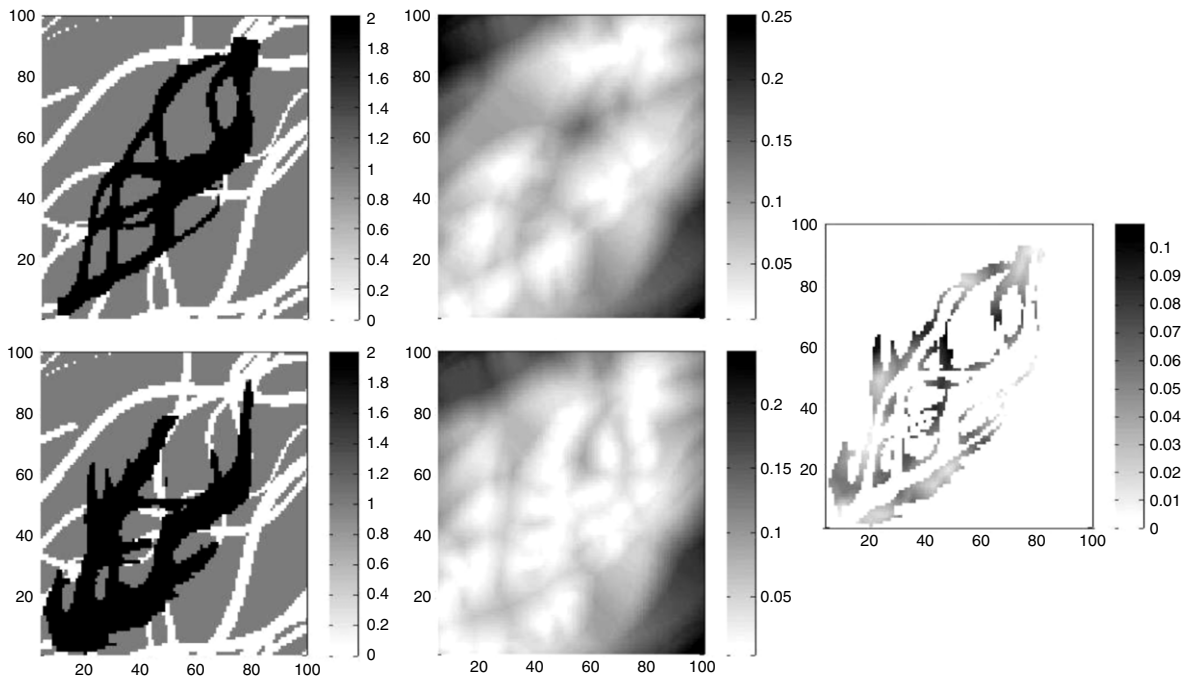


Fig. 7. Local dissimilarity map for the channelized reservoir case. Left: model M1 (top) and model M2 (bottom) after three-class segmentation. Middle: distance transform of model M1 (top) and M2 (bottom). Right: local dissimilarity map between model M1 and M2.

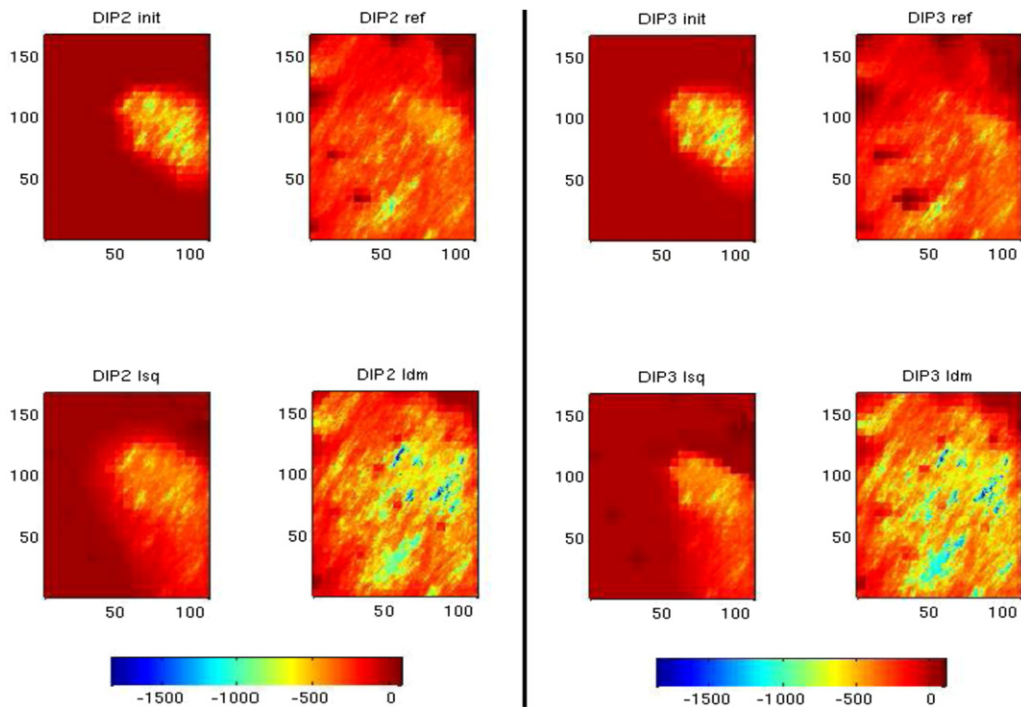


Fig. 8. Comparison of the optimal models with the LSQ and LDM objective functions. Left side: P impedance variations (DIP2) at time t_2 . Right side: P impedance variations (DIP3) at time t_3 . Initial map (top left), reference map (top right), optimal LSQ model (bottom left) and optimal LDM model (bottom-right).

and delimited by a fault in the south and the east. A small gas cap is located in the center of this dome-shaped structure. The geological model is composed of five independent unit, three of good quality (units 1, 3 and 5) and two of poorer quality. Initially, the field contains six production wells located around the gas–oil contact. No injection wells are required due to the

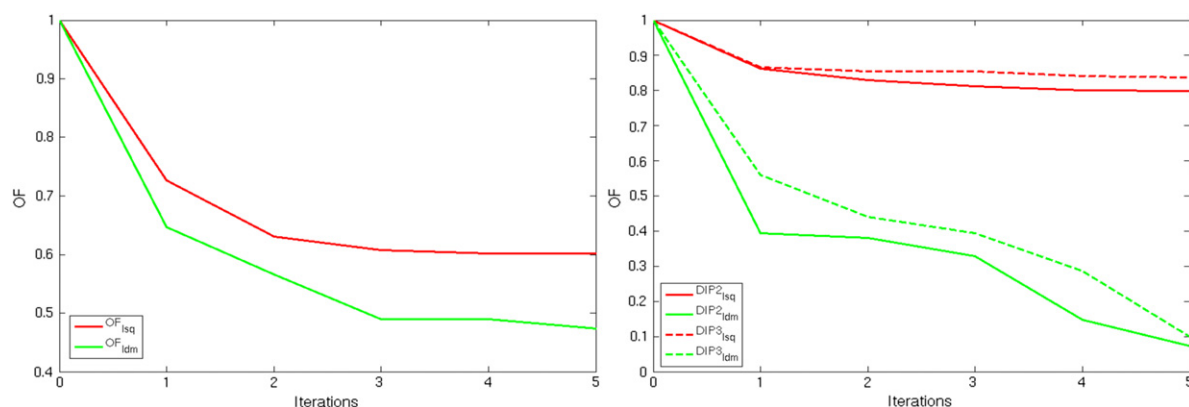


Fig. 9. Evolution of the objective function during the history matching process. Left: Global objective function. Right: Objective function of P impedance variations at times t_2 and t_3 .

strong aquifer. The dynamic data have been collected over 18 years. These dynamic data are pressure and oil flow rates at wells as well as 4D seismic data repeated at three times t_1 , t_2 and t_3 . We assume that the reservoir parameters are the mean porosity and the horizontal and vertical permeability inside each unit. This leads to 20 parameters for the whole model. We build a reference case by imposing some values on these parameters, and we collect the corresponding reference dynamic data. Now, we assume that the 20 parameters are unknown. Our goal is to adjust their values in order to reproduce the reference dynamic data. We then investigate the behavior of the least square (LSQ) and the LDM formulation. Note that in both cases we use a quasi-Newton algorithm for the minimization of the objective function.

First, we compare the optimal model obtained by both formulations. In particular, we compare the P impedance variations at t_2 and at t_3 given by the two optimal models. Fig. 8 shows a 2D horizontal cross-section of P impedance variation maps at times t_2 and t_3 obtained by the initial model (top right), the reference map (top right), the optimal LSQ model (bottom left) and the optimal LDM model (bottom right). The maps generated by the LSQ model are nearly the same as the maps given by the initial model. Conversely, the maps given by the optimal model with the LDM formulation reproduce the heterogeneities which appear in the reference maps.

Second, we compare the evolution of the objective functions during the history matching process in Fig. 9. After five iterations of the optimization method, the decrease of the objective function with the LSQ formulation is about 40%, whereas the decrease of the objective function with LDM formulation is about 55%. Moreover, if we look at the evolution of the objective functions by terms illustrated in Fig. 9 at the right, we see that the LDM formulation is able to decrease by 90% the errors on P impedance variations at times t_2 and t_3 whereas the decrease of the LSQ formulation is only 10%.

This example clearly illustrates that the LDM formulation is able to retrieve the 4D seismic attributes. It also decreases faster during the matching process.

4. Conclusion

In this paper, we propose a new formulation of the objective function for better incorporation of 4D seismic data into reservoir models. Since the standard least square distance is not representative of the visual difference between seismic images, we investigate the potential of a new discrepancy measure based on image processing tools. The main idea is to simplify seismic images in order to extract relevant information. Filtering is the first step of the proposed procedure. After a comparison of several filters on reservoir examples, we conclude that the NL means algorithm developed by [6] is the most efficient filter for seismic images. The main features of the filtered seismic maps are then extracted with segmentation techniques. More precisely, we focus on level-set methods introduced in [8,7]. The choice depends on the number of regions to be identified and consequently on the reservoir case under study. Finally, simplified images are compared through a local dissimilarity map, which is based on the computation of the local Hausdorff distance between the detected features. Unlike the least square approach, such a distance involves a spatial analogy between geological structures or fluid displacement. The application of this new formulation on a synthetic history matching case demonstrates its efficiency. Future work will focus on evaluating this approach on more complex and realistic reservoir cases.

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