Binary 4D Seismic History Matching, a Metric Study

Romain Chassagne\textsuperscript{1*}, Dennis Obidegwu\textsuperscript{1}, Julien Dambrine\textsuperscript{2}, Colin MacBeth\textsuperscript{1}

\textsuperscript{1} Institute of Petroleum Engineering, Heriot-Watt University, United Kingdom
\textsuperscript{2} Applied Mathematics Department, Poitiers University, France

* Corresponding author; Email address: romain.chassagne@pet.hw.ac.uk

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.

Keywords: objective function; seismic history matching; binary; metric; search landscape.
In reservoir engineering, history matching (HM) is an important and necessary process to update the reservoir model and get more accurate predictions to enhance the field management planning (Schulze-Riegert and Ghedan 2007). This goal is achieved through well history matching (WHM), which is the conventional option. During the past few years, the combination with seismic data called seismic history matching (SHM) is now an active research area, and the well production data is considered as a reliable piece of information from the field which can be used to update the simulation model. The real challenge with SHM (Fig. 1) is the incorporation of 4D seismic data into the reservoir simulation model (Landa and Horne, 1997). This can be incorporated at different domains of the HM workflow as described in Stephen and MacBeth, 2006. Mainly, there are three ways to proceed, through inversion processes, in the seismic domain (Landrø, 2001), or the impedance domain (Ayzenberg et al. 2013), or the saturation model domain (Falcone et al. 2004). The aforementioned methods are challenging owing to their complexity and above all they are time consuming. Some ways to circumvent these methods 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 the seismic gas maps be converted to binary maps such that the history matching is processed through a binary objective function.

With the binary map SHM setting and more specifically the optimisation process, the most intriguing question would be what the effect of different thresholds would have on the search space; and indeed a prior understanding of the influence of the threshold could help to enhance the methodology. Further thoughts would be whether there are any optimisation methods better adapted to search in this particular space than others, or if the search space is simpler to explore in the case of binary maps. On another note, the binary objective function defines the precision of the resulting history matching exercise, so one would need to think carefully about what the threshold should be. Also, what information is lost when a threshold is set up, and is there any added value in using two or more thresholds instead of one (binary)? These questions may sound trivial but they are a part of the in-depth understanding of the method. Another important issue is the technique in measuring the
similarity or dissimilarity between two images, because in most history matching studies, a choice is made with regards to the metric, but rarely is a strict comparison analysis conducted. On this aspect it is proposed to confront and analyse different metrics in the context of binary maps in order to evaluate image matching in different scenarios. As with real datasets, one can be confronted with different scenarios to capture; for instance, gas expansion, dissolution and displacement, therefore a suitable metric should have the capacity to properly evaluate these differences. In this work, some well-known metrics will be compared to the recent Current Measure Metric (CMM) (Glaunes et al., 2008 and Chesseboeuf 2015) in the context of the binary methodology to history match (well + seismic) a synthetic and a real field dataset. The CMM, specifically adapted to binary images, will be introduced as it is new to the geosciences community, although it has been used with success 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 a seismic history matching process such that it will be less costly in terms of computational time and processing of data as compared to a full seismic history matching with real data; moreover, doing this will aid in simplifying the analysis of the binary optimisation process. This exercise is to test (see part 2.3) the behaviour of the clustering method in different cases of gas exsolution. To this end, four idealised models are set up, which have been designed to capture the main characteristics of the gas maps and four images are to be used as the observed seismic images. The idealised models are defined with a summation of Gaussian functions highlighted by the gradient density, in order to mimic the gas map representation. Indeed after several map extractions from the real case (discussed later in this paper) we could define the gas exsolution and characterise the main patterns generated in a history matching process. The four resulting models have been inspired and designed, with a different size and spatial location of the gradient density. The four
models from 1 to 4 are classified from the simplest to the more diverse respectively in Fig. 2. The model 1 has a centred gradient density, given through the equation (1)

$$F_1 = e^{(-ax^2- by^2+E)} \quad (eq1)$$

Where, x and y are the spatial variables defined on x, y = [-2,2], a and b which represent the solution space are the uncertain parameters to be varied in the SHM process, and E stands for the perturbation. The corresponding seismic image is generated from eq1, where $a = a_0 = 0.99$ and $b = b_0 = 1.85$ are constants. Indeed the seismic images are generated from their corresponding idealised model as seen above, with an addition of a perturbation, in order to make the seismic and the idealised model image different. The perturbation in the seismic image has been generated with the addition of an alteration function of the corresponding idealised model in order to avoid the optimisation algorithm getting a perfect match during the history matching process. It should be noted that the alteration function is not a simple transformation (translation or rotation), but a modification of a particular axis of the Gaussian function. Having eq.1 with $E = 0$ describes the equation of the model and with $E = 0.8xy$ describes the corresponding seismic image. With model 2, we add a second decentred gradient density, model 3 showcases a modified version of model 2, and finally model 4 has a more complex gradient density feature (meaning the Gaussian altitude is lower); their corresponding equations are given in appendix A. The optimisation algorithm used to history match the four idealised models and their corresponding seismic data is the genetic algorithm. The extracted maps from the model and the seismic data are then filtered out with different levels of threshold (Fig. 2), and this is achieved with a method of clustering, which is the k-means algorithm described below.

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, in other words it is a method of simplifying the map and keeping only the main features (Tillier et al., 2013). In this case, the main feature is exsolved gas which can be characterised from the impedance seismic attribute as high values (Calvert et al., 2014). To further explain, a binary map is a reduction of the level of
information, and there are two levels for one threshold, these levels define different zones on a map (see Fig. 2). The method of selecting these areas/zones is a very key process which has to be done properly as the optimisation (history matching process) will be performed on these maps and a good update of the model would mainly depend on the zone selection. The threshold process can be performed manually by an engineering judgement screening, meaning that the threshold has to be sought such that it reflects the physics of the phenomena to be captured; however such a manual task is time consuming and non-unique. So as to remove these flaws, the $k$-means algorithm is used to identify clusters and then automatically extract the relevant information. $k$-means algorithm (MacQueen, 1967) is a classical method based on the concept of separating data by clustering points close to each other. The $k$-means clustering algorithm has been applied to a real dataset (see section 5.1), and the generated result has been compared to the result after an engineering judgment screening. The comparison example is visible in Fig. 3 and it shows that the maps are almost identical.

2.3 Binary map in a nutshell

Fig. 2 shows the comparison of the generated maps for different threshold levels. This leads us to conclude that the features of each model have been adequately captured, and there is no significant difference between the different levels of threshold, in terms of capturing the main characteristic of each pattern from each model. Therefore, the binary map (two level) seems to be as representative as a three or four level threshold when considering the four chosen idealised models presented here. The model 1 which is a 2D Gaussian function (eq.1) has been used to develop this study. The following section is on a discussion about model 1 only, however the same analysis is performed on models 2, 3 and 4, which in fact leads to the same conclusion. The SHM exercise in this case matches the realisations generated by model 1 and its corresponding generated seismic image (where for seismic, $a = a_0 = 0.99$ and $b = b_0 = 1.85$ and $E = 0.8xy$ in eq.1).
Fig. 4 shows a cross section of the search space of model 1, it displays the shape of the landscape an optimisation algorithm will have to explore in order to find the global minimum. Each of the four lines in Fig. 4 correspond to different thresholds, they present the same trend but not the same shape. Plateaus and sharp edges are observed with the use of one (binary map), two and three thresholds. An increment in the number of thresholds yields an increment in the number of plateaus and a reduction in the plateau size; when there is no threshold, the plateaus disappear and the graph becomes very smooth. The local geometry of the search space is affected by the number of thresholds, and this result is characterised by the emergence of rugosity (plateaus and sharp edges). In the case of a very fine grid, the conclusions previously drawn still stand; a finer discretisation just smoothens out the global landscape, but locally, the plateaus are still present. This exercise reveals that a gradient type algorithm might be unsuitable for a binary approach as it could get stuck on the local minimums. Therefore, optimizing a binary map is not necessarily simpler than a more traditional image composed of several levels of threshold. A recommendation could be to use a derivative-free optimisation algorithm in order to avoid such challenges. With respect to the context of binary seismic assisted history matching, the necessity to measure differences between images, as well as taking into cognisance the constraints highlighted previously, it is recommended that the selected metric should be globally sensitive, so as to compensate for the local ruggedness of the landscape. A history matching process is then conducted with the four idealised model equations and their corresponding images, the standard deviation for each case is measured (Fig. 5). The standard deviation expresses the difficulty in finding the corresponding best solution for the chosen optimisation algorithm. One key observation is that an increase in the number of thresholds leads to less variability in the solution, and that the standard deviation rapidly decreases when there is more than one threshold. Also it is noticed that there is a difference in the standard deviation values when using one threshold as opposed to the use of multiple thresholds. It is further seen that binary maps are less precise in terms of finding the best solution, and adding just one more threshold increases the precision. In other words, dealing with binary maps is clearly a different problem to solve as compared to dealing with more than one threshold. Comparing the different curves, model 3 has the highest standard deviation and this could imply that there are some models which are more suitable for binary mapping, and these would be
models with a very low standard deviation, like models 1, 2 and 4. This suitability refers to the models being less sensitive in terms of the variability of their solution space. Therefore a way to characterise and define the suitability of the search space of a simulation model could be developed, but doing such a characterisation could be very arduous and time consuming to obtain, especially for a real dataset.

3. A metric study

Multiple different maps scenarios are generated from the optimisation algorithm during the history matching procedure and these are compared to the observed seismic data. This comparison is done through the objective function and more specifically it is achieved with a metric (Fabbri et al., 2008) which defines how similar the images are (Mahalanobis, 1936) and from the degree of similarity a decision is taken to keep the corresponding set of parameters as a good update of the model. In the reservoir engineering community, this is generally done with a least square function. In this study, four different metrics are proposed to measure the similarity between two maps in order to ascertain the pros and cons of the different chosen metrics. The aim is to determine which of these metrics will be the best suited for a binary seismic assisted history matching exercise. The selected metrics consist of three popular metrics: the Hamming distance, Mutual information, the Hausdorff distance and then the Current Measure Metric (CMM). The latter is a fairly new metric that will be described, but the others are well known and have been used for several years (Zhao et al., 2005, Himanshu and Anamika, 2014, Rivaz et al., 2014) and they will serve as references in order to make a comparison on performance.

3.1 Description of the chosen metrics

3.1.1 The metrics which serve as references
Let us consider two images $A$ and $B$, which have the same dimension $N$, where $i, j$ are the coordinates of each pixel of image $A$, and $k, l$ are the coordinates of each pixel of image $B$. These images would be used as references in the definition of the metrics below.

The hamming distance (Hamming, 1950) is a metric which was initially used as a code error search and then widely used as a similarity metric, and has been studied in the theory community by Marvin and Seymour (1969) and Green et al. (1994), for more recent work see, Himanshu and Anamika, 2014. Its principal characteristic lays on counting the number of different pixels between the two images. The definition is as follows:

$$H_{am} = \# \{(i,j)|A_{ij} \neq B_{ij}\}$$

Hausdorff distance is the maximum distance of an image, $A$ to the nearest point in an image, $B$. It is a classical tool for image comparison as is seen in Huttenlocher et al. 1993 and Sim et al. 1999, recent use for image matching can be found in Zhao et al., 2005. The algorithm is as follows:

$$H_{au} = \max\{\text{dist}(A,B), \text{dist}(B,A)\}$$

with

$$\text{dist}(A,B) = \max_{(i,j)} \left\{ \min_{(k,l)} \sqrt{(i-k)^2 + (j-l)^2} \right\}$$

being the Euclidean distance between the pixel $i$ and $j$.

Mutual information is from the information theory domain (Shannon, C. E., 1948), and is a widely used metric (Russakoff et al., 2004; Rivaz et al., 2014). The fundamental quantity of information theory is defined as a functional of probability distribution. It is a measure of the amount of
information that one random variable contains about another random variable. It is the reduction in
the uncertainty of one random variable due to the knowledge of the other. It is defined as follows:

\[ MI = H(A) + H(B) - H(A, B) \]

with \( H(A) \) and \( H(B) \) being the individual entropy of image A and B respectively, and \( H(A, B) \) being the
joint entropy. More details about the above formula can be found in MacKay (2003).

3.1.2 The Current Measure Metric

The Current Measure Metric (CMM) introduced in Glaunès (2008) for computational anatomy is an
alternative tool for the calculation of distances between closed curves or surfaces. It can be likened to
an attempt to capture the shape of an object in a dark room using a single light by varying intensity,
orientation and angle. To explain this metric, different properties of a magnetic field (orientation,
location, intensity) are tested in order to capture the shape of an object.

More specifically, the main idea of CMM is to identify any shape to a mapping that returns the value
of the circulation of any vector field along the curve. This mapping is called a measure, and for each
given curve, an associated measure is obtained. It is possible to mathematically define a notion of
distance on these measures, which in many cases have proven to be efficient at quantifying the
differences (deformations, translations) between curves. In Glaunès (2008), this method was initially
intended to be used on parametric curves (or meshes in 3D), hence an extraction step was necessary in
order to use it. It has been shown in Chesseboeuf (2015) that it is possible to skip the curve extraction
process in order to work directly on images. The resulting CMM distance between two images can be
computed as the Euclidian norm of a filtered difference between the two images. The filter in question
is linear, hence defined (through convolution) by a Kernel function \( K_p \), where \( p \) is a parameter which
tunes the amount of smoothing applied. As with all the kernel based norms, the CMM can be
computed as:
\[ H_{CMM} = \sum_{i,j=1}^{N} K_{ij} |\widehat{A}_{ij} - \widehat{B}_{ij}|^2 \]

Where \( \widehat{A}_{ij} \) and \( \widehat{B}_{ij} \) denote the (i,j)-th Fourier coefficients of A and B, and K is the aforementioned kernel. More specifically, in order of having a Current-based norm, the following kernel is used (see Chesseboeuf (2015) for more details):

\[ K_{ij} = (i^2 + j^2)^2 \left( 1 + \sqrt{i^2 + j^2} \right)^{-p} \]

Where p is the smoothing parameter mentioned earlier. When p is small the norm becomes more local, which means that differences in details are well measured, but large translations are not seen. As p becomes large, the norm becomes smoother and small details are missed while large displacements are well measured.

### 3.2 Results on selected scenarios

In the context of seismic history matching, two images will be compared; a source/reference image which is the observed seismic data, and a target image which is the output from the simulator constrained by the input parameters decided by the optimiser. To compare these metrics, five scenarios (Fig.6) have been designed in order to determine their efficiency and reliability for our purposes. These scenarios have been created in the context of our real field application, which is a gas map exsolution phenomenon (an example is visible in Fig.3). Principal characteristics of the gas maps have been identified from the maps given by the optimisation process of a North Sea field dataset, and this enables us to identify and categorise them into five different groups, the expectation would be for the metric to be able to decipher these different categories. The first scenario is about isolated clusters. Sometimes the optimiser generates an isolated cluster of points from a new set of input parameters. It is expected that a suitable metric will be able to identify them as not being a part of the observed seismic data. The second scenario is about noise. A suitable metric must identify noise as an artefact.
and not a good option to update the model. As in some cases, noise could be small and sparse, it is quite challenging for some metrics to adequately capture it. The third is a growing shape. In other words, the ability for the metric to identify a shape that is roughly the same shape but with a different size. The fourth scenario is about the same concept as the previous scenario but for the capability to identify displacement of a shape. So far, individual potential scenarios have been elaborated to be quantified through the metric. However, during the optimisation process all these scenarios are often combined to different degrees; therefore, a final fifth scenario is analysed which is not about an individual potential scenario, but a combination of all the aforementioned scenarios. Indeed a metric could characterise some individual scenarios very well, but would not perform well when they all occur at the same time. On the other hand, a metric that can identify a mixed scenario could probably be badly suited to characterise only one of them. Therefore this fifth scenario has to be regarded as just an additional scenario as it is necessary to cover all the range of possible scenarios generated during the history matching process.

The results for these scenarios are summarised in Fig. 7. In the first scenario, all metrics give valuable information, except Hausdorff distance which is unable to identify isolated points at all, regardless the case. The second scenario is about testing the sensitivity to noise. As this has quite a similar characteristic to the first scenario, almost the same results are obtained, implying that the Hausdorff distance is not adapted to identify random isolated points on a grid. For the third scenario (growing shape), three metrics obtain good results except Hausdorff distance which classifies case number four as being less different than case number three. This is wrong, and the other metrics correctly identify the sequence of the two cases. On the shape displacement test in the fourth scenario, the Hamming distance and mutual information fail to identify differences after case number four. Finally with the fifth scenario (the combination of scenarios), mutual information fails for the last case as the metric evaluates that case number six is less different than case number five. Also Hausdorff distance does not get satisfactory results at all. CMM also has a very slight misjudgement with case number six which is acceptable. An enhancement of this result can be made by changing the parameter p which is
the sensitivity to measure details to $p=2$ instead of $p=4$, and this corrects the evaluation of the CMM, and the result is correct for the fifth scenario. This new value of $p$ is not the best suited for the other scenarios and could lead to less efficient evaluation. Depending of the scenarios, $p=4$ seems to be the optimum choice. Each metric is more adapted to capture some features better than others, but overall CMM was shown to be the only metric capable of perfectly analysing all the scenarios, with Hamming distance being the second best metric of this study.

4. Application of the Hamming distance and the Current Measure Metric on a synthetic dataset

4.1 Description of the synthetic dataset

The previous part selected the two most effective metrics in a binary mapping context, which are the Hamming distance and the CMM. Before applying them to a real dataset, another comparative test will be performed with these two metrics on a synthetic field. The purpose here is to test the two metrics in a controlled reservoir setting, therefore a replicate of gas exsolution is designed. The synthetic dataset used is a modification of ETLP model, which is a synthetic dataset that was recently used by Fursov, 2015, and is built off the characteristics of a turbidite field from the United Kingdom Continental Shelf (UKCS). The reservoir fluid is black oil with an API gravity of approximately 25° (medium oil) at a temperature of 120°F (48.89°C). Initial reservoir pressure is approximately 3620 psi (24.96 MPa) (at depth 1510m TVDSS) whilst bubble point is 2970 psi (20.48 MPa) at the top reservoir level, and the solution gas-oil ratio ($R_s$) is 385 scf/bbl (68.52 sm$^3$/m$^3$). It is a three phase reservoir penetrated by two vertical wells – a producer well and an injector well, that are controlled by liquid rate. The reservoir has an average thickness of 35m (115ft), and heterogeneous properties (horizontal permeability, vertical permeability, porosity, NTG) as shown in Fig. 8. The figure also shows the plan view and cross sectional view of the model, the position of the injector and producer, as well as the small water saturated zone penetrated by the injector. The field operational period is 500 days, and the production/injection plan is adjusted as required to replicate the combination of gas
exsolution and water evolution. There are two seismic surveys generated – a baseline seismic survey
prior to production start (Day 0), and a monitor seismic survey at the end of the field operational
period (Day 500). The seismic surveys were generated by seismic modelling according to the
procedure specified in Amini 2014, using the petro-elastic properties, seismic wavelet and rock stress
sensitivity of a typical UKCS field. The Sum of Negative Amplitudes (SNA) between the reservoir
top and reservoir base horizons is used as the seismic attribute, and this attribute is selected in order to
be consistent with what was used in the real field application. The geological model of the dataset has
114 x 38 x 30 cells with approximate thicknesses of 10m x 10m x 1m in the X, Y and Z direction
respectively, while the simulation model has 57 x 19 x 4 cells with approximate thicknesses of 20m x
20m x 8m in the X, Y and Z direction respectively.

4.2 The gas exsolution scenario and results

The initial reservoir pressure is above the bubble point pressure, hence there is no initial gas cap in the
reservoir. In order to develop a scenario whereby sufficient gas is exsolved from the oil in the
reservoir, the reservoir is depressurized by putting the producer well on stream for 500 days at a
constant liquid rate of 630 stb/day (100 sm³/day), and as there is no need for pressure support, there is
no injector well activity. The initial simulation model (base case) is perturbed in ascending order of
complexity. This is achieved by perturbing the reservoir absolute permeability with multiplier values
of 0.8, 0.6 and 0.4 (Fig. 9). In the base case 4D (monitor minus baseline) model, gas is exsolved
around the producer as the reservoir goes below the bubble point pressure. Once the gas attains its
critical saturation (saturation at which it becomes mobile), it accumulates at the local high due to its
density property and gravity effect. The gas can then be seen migrating from the right side to the left
side through the centre, and this is due to the nature of the reservoir structure, as well as the pressure
gradient. The corresponding binary maps have been generated using k-means algorithm. Perturbing
the base case model by incrementally reducing the permeability increases the exsolved gas swept
from the right side to the left side, and these spatial gas changes will be analysed by the two selected metrics.

The binary 4D seismic map is compared to the base case binary gas saturation 4D map and to the perturbed binary gas saturation 4D maps using the Hamming distance metric and CMM. The perturbations are labelled A to D, where A is the comparison of the binary 4D seismic map to the base case binary gas saturation 4D map which gives a perfect match, all through to D which is the comparison of the binary 4D seismic map to the binary gas saturation map of the model whose permeability has been multiplied by 0.4 which gives the least perfect match. The plot of the misfit (Figure 10) shows a similar and correct response from both metrics, where perturbation D has the highest misfit, and this misfit gradually reduces to a misfit of zero for perturbation A which represents the initial base case starting model. The Hamming distance has an approximately linear misfit profile, while the CMM has an approximately non-linear misfit profile as already observed in the previous part of this paper. This result of a linear vs non-linear misfit behaviour in a more physical context leads to think that CMM seems to have the ability to capture a non-linearity characteristic as expected in a real world problem. As a consequence, the ability to measure a non-linear response to a non-linear context should be noticed as a strength of CMM as compared to the Hamming distance.

5. Application of the Hamming distance and the Current Measure Metric on a field dataset

5.1 Description of the field dataset

The dataset is from a field in the UKCS, the complex reservoir comprises a sequence of multiple stacked deep marine silicilote turbidites with porosity of 25-30% and permeability of 200-1000mD. Each reservoir is composed of channels, amalgamated channels and sheet-like sands. The field is heavily compartmentalised with faults cross-cutting turbidite sand depositional axes. It contains black oil accumulations close to bubble point, and its drainage strategy is by water injection using down-dip
injectors and up-dip producers (Martin and Macdonald, 2010). In this field there is gas liberation, mobilisation, and then repressurisation with subsequent dissolution. During the course of production, poor connectivity led to a lack of pressure support from injectors; this combines with a weak aquifer influx to give a strong pressure decrease in some areas, and a drop below bubble point with the consequent liberation of free gas. The drilling plan was adjusted for this reason and the reservoir recovered the pressure (Govan et al. 2005). There are multiple vintages of seismic shot across this field for reservoir management purposes, and for our current work the preproduction baseline in 1996 and six monitors shot in 1999, 2000, 2002, 2004, 2006 and 2008 have been selected. These data have been cross-equalised by the operator for 4D seismic interpretation purposes, and have a non-repeatability NRMS noise metric (Kragh and Christie 2001) of approximately 31% (Falahat et al. 2011). An isolated sector is identified for study that is segmented by two major EW trending normal faults.

5.2 History matching of the field dataset

Hamming distance and CMM have been selected for the following study as they performed best in the tests conducted in the previous part of this paper. An evolutionary search algorithm has been used on 35 parameters, these parameters have been selected after a sensitivity analysis (Latin hypercube) on 104 parameters. It should be noted that an identical SHM workflow has been utilised for both metrics.

Fig. 11 presents an avenue to compare the results of updating the model using the two selected metrics in a quantitative way. The history matching is performed for the first four surveys (2500 days), while a forecast analysis is performed on the subsequent two surveys (1500 days). The observed seismic data shows information of small clusters scattered in some areas, while the base case model shows few isolated cluster of points that need to be updated. The comparison of the updated binary map with the Hamming distance and the CMM can be decomposed into two parts.

For the first three surveys, the two metrics have approximately the same behaviour, with two main clusters localised in the same area, which is very comparable to the seismic binary map in terms of
dimension and localisation in space. For the next three surveys, gas is decreasing and the clusters in the seismic binary map start to scatter, and this same trend is noticed for the Hamming distance and CMM, except that the latter tends to keep a cluster-type structure. This trend is maintained for the last two surveys, as it is shown that overall Hamming distance does not generate a cluster-type as compared to CMM that generates clusters that vary in size. This phenomenon is what previously was referred to as a more global metric as opposed to a local metric.

What has been done so far is a qualitative analysis in order to understand the behaviour of both metrics in terms of their ability to capture the features. This approach doesn’t really identify which metric is more efficient in terms of producing a good update of the simulation model. The following part is then about the SHM procedure from a quantitative point of view. The history matching performance is usually evaluated through the forecasting ability of the production well data.

For this exercise, two wells are selected, P1 (fig.12) and P2 (Fig.13), and the oil, gas and water production rate are analysed. The first part of the historical production data is used to update the model and the subsequent part is used to evaluate the capability of the updated model to forecast the future production. Concerning well P1 (Fig.12), CMM reduces the uncertainty for oil/gas/water production in the improved models for the history and forecast, and this is particularly evident for the gas production.

Regarding well P2 (Fig.13), this observation is less obvious as an evident improvement of the updated models is not observed. The percentage improvement of the model predictability relative to the base case is then calculated. It is calculated that there is a 21.6% improvement with Hamming distance and 25.84% with the CMM; therefore using CMM gives a slightly better improvement of the simulation model update. In Fig. 14, the speed of convergence is investigated with the CMM and the Hamming distance metric, using a plot of the objective function versus the number of iterations. In this particular case, the CMM shows an improvement on the convergence speed. In seismic history matching, many reservoir simulations runs are required, and each of them could be extremely
computationally expensive, running from hours to weeks, therefore even a small gain in the convergence could be a valuable benefit in the end of the overall history matching exercise.

6. Conclusion and future work

This paper describes the construction of a methodology for binary objective function in the context of a time lapse seismic history matching technique. Firstly, an analysis on the optimisation search space for a binary map has been conducted. The results show that the search landscape does not change on the large scale but changes quite significantly locally, and this would have a direct impact on the optimisation algorithm that may be suitable; hence, derivative-free methods are recommended in the case of one threshold (binary).

Moreover the study shows that one threshold is enough to capture the shape of a gas map, and that it possesses enough valuable characteristic information to allow a reasonably good optimisation process. As the number of threshold is increased, the optimal result from the optimisation is easier to find. The thresholds act like filters to refine the search space. A new domain of application for the Current measure metric (CMM) is presented, and it is compared to other well-known metrics, in the context of 4D seismic history matching with binary maps.

The theoretical conclusion made in the first part of the study is compared to the result on the real field data, and the conclusion still stands although the real field data’s conclusion is not as definite. In other words, the present study exhibits that the Hamming distance performs quite well despite its simplicity and the CMM with its higher complexity does better but not in a drastic manner. However the theoretical and synthetic studies shows that the CMM performs better than the other metrics, the real strength of this metric shown from the selected scenarios is that it has the ability to detect various sets of different scenarios, and looks very adapted to gas map analysis as it is an adjustable global metric type. This means that this metric could be used with more confidence for a broader range of fields and attributes to identify. For instance, for a different geology, and for application to water and gas, as all these different combinations lead to different patterns to identify. As every field is quite unique,
having a metric with “sharp eyes” is definitely required. This result leads us to envisage an adaptive
fine tuning of the CMM, depending on the data at disposal.

Moreover based on the overall performance of the CMM, it can be concluded that it possesses the
potential of delivering a significant improvement during a seismic history matching exercise on a real
dataset. Finally, due to its smoothing nature, which can be tuned with the parameter p, the CMM has
the ability to suppress the observed rugosity (see Fig. 3) of the search landscapes during the matching
of binary images which enhance the optimisation process.

Also a future work to be done will be to apply a seismic history matching workflow to water and gas
scenarios, and evaluate the added value of the CMM. A comparison with traditional (not binary) SHM
would be legitimate as well.

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Appendix

Equation of the idealised models and corresponding seismic image.

E=0 for the equation of the model and E=0.8xy for the corresponding seismic image.

\[
\begin{align*}
x, y &= [-2, 2], \quad a_0 = 0.9954, \quad b_0 = 1.856 \\
F_1 &= e^{-a_0 x^2 - b_0 y^2 + E}
\end{align*}
\]
\[ F_2 = e^{-a_0 x^2 - b_0 y^2} + e^{-a_0 (x-1)^2 - b_0 (y-1.6+E)^2} \]
\[ F_3 = e^{-a_0 x^2 - b_0 y^2} + e^{-8a_0 (x-0.8)^2 - b_0 (y-1.2+E)^2} \]
\[ F_4 = e^{-a_0 (x+1)^2 - b_0 (y+1.2)^2} + e^{-a_0 (x+1)^2 - b_0 (y+0.8)^2} + e^{-a_0 (x+1)^2 - b_0 (y+0.2)^2} + e^{-0.2a_0 (x-1.2)^2 - 0.2b_0 (y-1.6+E)^2} \]

References


Martin K. and MacDonald C., 2010. Schiehallion Field: Applying a geobody modelling approach to piece together a complex turbidite reservoir. 7th European Production and Development Conference, Aberdeen, UK.


Fig. 1. Workflow of the (4D seismic + well) history matching process used.
Fig. 2. Test cases for model 1, 2, 3 and 4 with different threshold levels. Four levels of threshold are presented from the top to the bottom, the last one (d) has no threshold, which corresponds to the CPU precision (meaning that it is the floating point number precision that defines the maximum attainable level of threshold).
Fig. 3. Considered binary gas map (top), filtered by $k$-means algorithm (middle) and filtering by engineering judgement (bottom).
Fig. 4. Cross section of the normalised search space applied to different threshold levels, one (binary map), two, three, no threshold (CPU precision, meaning that it is the floating point number precision that defines the maximum attainable level of threshold). Y-axis is the misfit and the X-axis represents a chosen parameter for the model1. This displays the misfit of the seismic history matching using model1. To obtain these curves, we fixed the parameter “a” (eq.1) and vary the other parameter “b” (eq.1) between 0 to 4. Different values of the fixed parameter “a” have been tried to check if the same features were obtained when we moved to another constant value of “a”.

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593
594  Fig. 4. Cross section of the normalised search space applied to different threshold levels, one (binary map), two, three, no
595  threshold (CPU precision, meaning that it is the floating point number precision that defines the maximum attainable level of
596  threshold). Y-axis is the misfit and the X-axis represents a chosen parameter for the model1. This displays the misfit of the
597  seismic history matching using model1. To obtain these curves, we fixed the parameter “a” (eq.1) and vary the other
598  parameter “b” (eq.1) between 0 to 4. Different values of the fixed parameter “a” have been tried to check if the same features
599  were obtained when we moved to another constant value of “a”.

Fig. 5. Standard deviation in Y-axis for the model 1, 2, 3, 4 as a function of the chosen threshold level from 2 level (which correspond to binary map), 3 level, 4 level and finally the full level (which correspond to the CPU precision), meaning that it is the floating point number precision that defines the maximum attainable level of threshold.)
Fig. 6. Different scenarios to test the metrics. From the left to the right, the evolutionary scenarios, which are getting more and more different from the source image (case No. 1) as we go from the top to the bottom. The first line, case No1 is the source/reference case. The dashed white line are fixed marks to help seeing the different transformations (growing, displacement, combination) in space.
Fig. 7. Results of the performance of the different tested metrics (Hamming distance, Current measure, Hausdorff distance, Mutual Information) on the different selected scenarios.
Fig. 8. Heterogeneous properties (horizontal permeability, vertical permeability, porosity and NTG) of the dataset. Also shown is the plan view and cross-section view of the model highlighting the location of the producer well and injector well, as well as the oil-water contact.
Fig. 9. On the left column, 4D seismic data response of the base case 4D model, base case 4D model gas saturation response, and perturbed 4D models (permeability perturbed) and the corresponding binary maps on the right column, in the gas exsolution scenario.
Fig. 10. The values of the misfit using the Hamming distance and Current metric objective function for the different cases of perturbed models for a gas exsolution scenario.
Fig. 11. Binary gas maps, the first column give us the state of the model in terms of gas distribution before SHM, the second column is the observed seismic data we want to tend to, the third and fourth column are the updated (after SHM) simulation model respectively using Hamming and the CMM.
Fig. 12. Production (oil, gas and water) history and prediction for well P1 after seismic history matching with the Hamming and CMM metric.
Fig. 13. Production (oil, gas and water) history and prediction for well P2 after seismic history matching with the Hamming and CMM metric.
Fig. 14. Convergence speed through the decrease of the objective function during history matching, with the CMM (red line) and the Hamming metric (blue line).