Non Uniqueness and Uncertainties in the Training Image to Seismic Image Transform

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Abstract

Seismic interpretation aims to predict reservoir properties such as lithology, porosity, and fluid saturation from seismic data. Reducing uncertainties in reservoir models requires data integration. In order to integrate seismic data with multiple-points (MP) geostatistics it becomes essential to quantify the links between training images (TI) and corresponding seismic images (SI), and to understand better the uncertainties associated with the TI to SI transform. In this paper, we address some of the causes of uncertainty in the relationship between TI and the associated SI.

The MP geostatistics simulation is completely dependent on the TI used, spatial arrangement of the units, and elastic properties assigned to them. However, we know that elastic properties of rocks change with spatial location and geological process (Avseth, 2006). For instance, compaction, diagenesis, cementation and sorting affect the porosity and elastic moduli of rocks and in general, different lithofacies can have different compaction and sorting trends. Moreover the seismic imaging provides a bandlimited, low-pass filtered version of the true subsurface. We explore how variations of rock properties scale of representation and channel shapes can give rise to ambiguities and uncertainties in the transform from TI to SI. Effects of variations in the scale of the TI features are evaluated. We quantify this uncertainty in terms of distance metrics (Scheidt and Caers, 2007) in the TI space versus distance metrics in the SI space.

1 Introduction

Training images (TIs) are used in Multiple point (MP)-statistics as a way to integrate geologic features, especially curvilinear ones (Strebelle, 2002). MP geostatistics is based on the concept of training images (TI) characterizing the spatial variability and facies patterns associated with different geologic environments. Since TIs are used to create geologic models consistent with the available well data, seismic data, and geological interpretation concept imposed by the multiple-point algorithm through the training image, it is important to quantify the links between TIs and corresponding SIs. In this paper, we address some of the causes of uncertainty in the relationship between TIs of fluvial channel and the associated SIs. The causes studied are divided into scale of feature representation, and channel morphology shown by the TIs. Both parameters are perturbed in the TI space and then evaluated in the SI space. Using dissimilarity distances for assessing how these perturbations affect on the transform (Suzuki and Caers, 2006) seems to be natural. The dissimilarity matrices are a high dimensional source of information, which makes the task of exploring the dissimilarity matrices in order to infer relationship a
difficult task. Hence, we reduce the data dimensionality using multidimensional scaling (MDS) to make this information suitable to a visual exploration. MDS is not only applied on the dissimilarity matrices obtained from TIs but also on the dissimilarity matrices obtained from the SIs. The links between both spaces are inferred through a visual comparison of the 2D-Euclidean spaces that represent almost exactly the dissimilarity distances. The representation in the Euclidean space is absolutely dependent on the distances used, hence we assess how three different distances (Euclidean distance, a specially defined pixel-wise distance, and Hausdorff distance) behave in detecting relationship in one space and between spaces.

The following sections describe the methodology used in the TIs construction and the process of populating them with realistic petrophysical and elastic properties. A brief description of the metric distance tools used in the transform evaluation is shown. All the applications carried out were run on a synthetic set of TIs presented here. We end this paper by discussing the result obtained and proposing new extensions of this work.

2 Training Images

TIs are essentially a database of geological patterns, from which multiple-point statistics, including the variogram, can be borrowed. The TI replaces the variogram in multiple-point geostatistics as a measure for geological heterogeneity. It contains MP information and, more importantly, is much more intuitive since one can observe, prior to any geostatistical estimation or simulation, what patterns will be reproduced in a set of multiple reservoir models (Caers and Zhang, 2002). Thirty-six TIs (generated in SBED using object-based techniques) are used throughout this paper. Every TI comprises of twelve channels. Each of these channels has the same center-line location in the different TIs. Only channel depths and widths change. The actual thirty-six images can be divided into 3 categories according to the resolution of the features that they show. There are twelve images at 1 by 1 meters resolution, twelve images at 3 by 3 meters resolution, and twelve images at 5 by 5 meters resolution. Figure 1 shows the first twelve images. They are numbered from 1 to 12 from upper left to lower right. We can see that the channel widths decrease top to bottom, whereas channel depths decrease left to right. The facies in blue, dark red, and light red correspond to shales, shaly sands, and clean sands respectively.
The rest of the TIs were built from the twelve TIs shown above (Figure 1) performing an upscaling to their respectively resolution. The upscaling was carried out by assigning the mode of facies within the gridcells at a given location being upscaled. Figure 2 shows how the TI #1 looks after this process. We see the changes in the sedimentary sequences that comprise the channels and in the channel-shale boundaries. In addition, this figure explains the relationship that exists among the first twelve images and the others twenty four images. TIs #13 to #24 and TIs #25 to #36 show the same channel morphologies to the TIs #1 to #12 but at resolution 3 by 3 and 5 by 5 meters respectively.

Figure 2: Training images #1, 13, and 25 at 1 by 1, 3 by 3, and 5 by 5 resolution respectively.

3 Petrophysical Properties

3.1 Porosity Simulation

Gaussian Sequential Simulation (SGS) was used to populate the channel model with realistic petrophysical properties considering the facies spatial distribution shown by each TI. Notice that the
The purpose of generating a petrophysical property model based on the TIs is to obtain from them the corresponding seismic images (Si) through seismic forward modelling. The simulations of each facies were not conditional to any specific data, but only conditional to target histograms. These histograms are different for each of the facies simulated, and all of them follow a Gaussian distribution with mean a variance shown in the Table 1. Different spatial correlations for different facies were considered by imposing a specific variogram model for each facies (Table 2). This is required due the fact that we expect the clean sands and shaly sands to have a better horizontal spatial continuity than the shales. The final property models were obtained using the cookie-cutter approach. Therefore the geology was honoured in the petrophysical populating process (Figure 3).

Table 1: Target histogram parameters.

<table>
<thead>
<tr>
<th></th>
<th>Mean [%]</th>
<th>Variance [%^2]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shale</td>
<td>6.0%</td>
<td>0.1%</td>
</tr>
<tr>
<td>Shaly Sand</td>
<td>27.0%</td>
<td>1.0%</td>
</tr>
<tr>
<td>Clean Sand</td>
<td>23.0%</td>
<td>0.1%</td>
</tr>
</tbody>
</table>

Table 2: Variogram models and parameters used in porosity simulation.

<table>
<thead>
<tr>
<th></th>
<th>Shale</th>
<th>Shaly Sand</th>
<th>Clean Sand</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variogram Type</td>
<td>Spherical</td>
<td>Spherical</td>
<td>Spherical</td>
</tr>
<tr>
<td>Nugget Effect</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>Ranges</td>
<td>1750/1750/70</td>
<td>5000/2500/10</td>
<td>3000/1750/20</td>
</tr>
<tr>
<td>Angles</td>
<td>0/0/0</td>
<td>90/0/0</td>
<td>90/0/0</td>
</tr>
</tbody>
</table>

Figure 3: TI #1 and porosity, density, and P-wave velocity computed.
3.2 Rock Density

Rock density is a function of the fluid density, the matrix density, and the rock porosity. Rock porosity and fluid density data are necessary since generally the pores are considered as totally saturated with fluid. Equation 1 shows the usual relationship between the previously mentioned variables.

\[
\rho = \phi \rho_{\text{fluid}} + (1 - \phi) \rho_{\text{matrix}}
\]  

(1)

We consider the rock matrix as a combination of different minerals. Therefore different mineral densities have to be taken into account in the rock density calculation. Equation 2 shows how the matrix density is computed. In this equation \( f_i \) is the fraction of mineral \( m_i \) with density \( \rho_{m_i} \) in the matrix.

\[
\rho = \phi \rho_{\text{fluid}} + (1 - \phi) \sum_{i=1}^{N} f_i \rho_{m_i}
\]  

(2)

Table 3 shows the density values of each mineral in the rock matrix.

<table>
<thead>
<tr>
<th>Mineral Density</th>
<th>Shale [%]</th>
<th>Shaly Sand [%]</th>
<th>Clean Sand [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clay</td>
<td>2.4</td>
<td>70</td>
<td>0</td>
</tr>
<tr>
<td>Quartz</td>
<td>2.65</td>
<td>20</td>
<td>70</td>
</tr>
<tr>
<td>Feldspar</td>
<td>2.63</td>
<td>10</td>
<td>20</td>
</tr>
<tr>
<td>Rock Fragments</td>
<td>2.7</td>
<td>0</td>
<td>10</td>
</tr>
</tbody>
</table>

3.3 P-wave velocity

We use the friable-sand model (Avseth et al., 2005) to compute the P-wave velocities (\( V_p \)) for the sand facies. In this model \( V_p \) is calculated following the usual equation for elastic waves:

\[
V_p = \sqrt{\frac{K + \frac{3}{4} \mu}{\rho}}
\]  

(3)

where \( K \) and \( \mu \) are the saturated bulk and shear moduli, and \( \rho \) is the corresponding saturated bulk density. The elastic saturated moduli are computed from the dry moduli using Gassmann’s equations. As explained in Avseth et al., 2005, the friable sand model consists of a modified Hashin-Shtrikman lower bound between the mineral end member and a granular pack end member at the critical porosity.
(depositional porosity). The dry moduli of the well-sorted end member at a critical porosity, given by the Hertz-Mindlin theory (Mindlin, 1949) as follows:

\[
K_{HM} = \left[ \frac{n^2(1-\phi_C)^2 \mu^2}{18\pi^2(1-n/2)^2 P} \right]^{1/3} \tag{4}
\]

\[
\mu_{HM} = \frac{5-4\nu}{5(2-\nu)} \left[ \frac{3n^2(1-\phi_C)^2 \mu^2}{2\pi^2(1-n/2)^2 P} \right]^{1/3} \tag{5}
\]

where \(K_{HM}\) and \(\mu_{HM}\) are the dry rock bulk and shear moduli respectively at critical \(\phi_C\) (i.e., depositional porosity); \(n\) is the coordination number, \(\mu\) and \(\nu\) are the shear modulus and Poisson’s ration of the mineral grains, and \(P\) is the effective pressure (in this case considered as the overburden pressure at 500 meters depth). For clastic deposits critical porosity is around 40%.

At porosity \(\phi\) the concentration of the pure solid phase in the rock is \(1-\phi/\phi_C\). Then the bulk and shear moduli of dry friable sand model mixture are given by the modified Hashin-Shtrikman lower bound:

\[
K_{dry} = \left[ \frac{\phi / \phi_C}{K_{HM} + 4\mu_{HM} / 3} + \frac{1-\phi / \phi_C}{K + 4\mu_{HM} / 3} \right]^{-1} - \frac{3}{4} \mu_{HM} \tag{6}
\]

\[
\mu_{dry} = \left[ \frac{\phi / \phi_C}{\mu_{HM} + z} + \frac{1-\phi / \phi_C}{\mu + z} \right]^{-1} - z \tag{7}
\]

where \(K\) is the bulk modulus of the mineral, and \(z\) is given by:

\[
z = \frac{\mu_{HM}}{6} \left( \frac{9K_{HM} + 8\mu_{HM}}{K_{HM} + 2\mu_{HM}} \right) \tag{8}
\]

The saturated elastic modulus \(K_{sat}\) can be calculated from the Gassmann’s equation:

\[
\frac{K_{sat}}{K_{min} - K_{sat}} = \frac{K_{dry}}{K_{min} - K_{dry}} + \frac{K_{fluid}}{\phi(K_{min} - K_{fluid})} \tag{9}
\]
whereas $\mu_{sat}$ is given by:

$$\mu_{sat} = \mu_{dry}$$ \hspace{1cm} (10)

The procedure described above is carried out to obtain velocities for sands and shaly sands facies. For the shales we utilize the Gardner’s power law (1974) relation, which uses the following empirical relationship between P-wave velocity and density for:

$$\rho = dV_p^f$$ \hspace{1cm} (11)

where the values used $d = 1.75$ and $f = 0.265$ are typical for shales. Figure 4 shows the relationship between $V_p$ and porosity for different facies that form TI#1. Data from different facies gather in well defined cloud-shaped groups in this plot. The scatter is explained by the fact that a 2% of random component was added in the velocity calculation for each facies, hence they do not follow a strict linear or power $V_p - \text{porosity}$ relationship.

![Figure 4: Vp v/s Porosity calculated using the TI #1.](image)

Also, the Hashin-Shtrikman upper and lower bounds are shown. These bounds allow us to check whether the $V_p$ values are in a valid range or not. Hashin-Shtrikman bounds are narrower than Voight and Reuss bounds, which are defined based on the stiffest and softest possible mixture of constituents of a rock. In the figure can be seen that the $V_p$ data obtained are located inside the bounds selected and also that the
stiffer rocks (rocks usually with higher density) tend to have higher $V_p$. Notice that there are data from different facies with different porosity but equal $V_p$, which clearly represent a source of uncertainty. In this paper rocks are considered as 100% water saturated, hence we use a $\rho_{\text{fluid}}$ is equal to 1 [g/cc]. Nonetheless a possible extension of this work is to consider different fluids saturating the rock, for which would be necessary to perform a fluid substitution on the water saturated properties in order to obtain elastic properties coherent with the fluid saturation condition suggested.

4 Forward Seismic Modeling

One dimensional normal-incidence convolutional modelling with lateral smoothing was used in order to obtain SIs from TIs. In this case the wavefront is considered as parallel to an interface and its raypath perpendicular, or normal, to the interface, this is the normal incidence approach. The top of the 300 meters thick TIs were set at 500 meters depth, therefore the facies models span from 500 to 800 meters depth. A 50 Hz central frequency was used in all the synthetic cases shown in this papers except when the purpose was to evaluated the importance of the seismic frequency in the forward modeling as will be discussed later. The TI to SI transform is illustrated in Figure 5 using TI #1 and SI#1. This figure highlights the importance of rock physics and waves propagation knowledge in understanding the TI to SI transform. Figure 6 shows SIs (SI matrix) obtained from the TIs showed in Figure 1.

Figure 5: Seismic images computed using properties from TI#1.
In the following sections we describe briefly the different distances used to quantify dissimilarity amongst the TIs and the corresponding SIs.

5.1 Euclidean Distance

The Euclidean distance between two images is computed using two vectors, which are obtained by reshaping the two image matrices into vectors. Figure 7 illustrates this process for TI#1.

For example, if two images A and B are comprised of N by M elements, the Euclidean distance between them is given by:
\[
A = (a_1, a_2, \ldots, a_{nm})
\]
\[
B = (b_1, b_2, \ldots, b_{nm})
\]
\[
d_{eu} = \sqrt{(a_1 - b_1)^2 + (a_2 - b_2)^2 + \cdots + (a_{nm} - b_{nm})^2} = \sqrt{\sum_{i=1}^{nm} (a_i - b_i)^2}
\]

5.2 Pixel-by-Pixel Distance

Since both TI and SI data are stored in two-dimensional matrices, it turns out to be natural to think of a distance that relates each element of the matrices. If we consider the images \(A\) and \(B\) defined as in the section 5.1, the pixel-wise indicator \(\delta_i\) between them is given by:

\[
\delta_i = \begin{cases} 
0, & \text{if } a_i = b_i \\
1, & \text{if } a_i \neq b_i 
\end{cases} \quad \forall a_i, b_i, \quad i = 1, \ldots, nm \tag{13}
\]

Therefore, the pixel-by-pixel distance between the images \(A\) and \(B\) is:

\[
d_{pbp} = \sum_{i=1}^{nm} \delta_i \tag{14}
\]

5.3 Hausdorff Distance

The particularity of Hausdorff distance is that it measures the similarity of points in two finite sets, but does not find a one to one correspondence between points in each set (Dubuisson M-P, and Jain A, 1994). If \(A\) and \(B\) are two set of points, the Hausdorff distances between them is given by:

\[
H(A, B) = \max_{a \in A} (\min_{b \in B} ||a - b||), \max_{b \in B} (\min_{a \in A} ||a - b||) \tag{15}
\]

where the term \(||a - b||\) is the distance between two points, or the norm of the vector from point \(a\) to point \(b\). In this paper the norm used is the Euclidean distance norm. Hausdorff distance is widely used in image recognition algorithms; however due the fact that multiple distances between the \((a, b)\) pairs must be computed in order to compare images, a simplification of images is required. This simplification generally consists of considering only the edges of features that an image shows. Therefore only the points that belong to these edges are taken into account in the distance calculation between the two sets of points (images). Hence, the channel edge recognition in the TI space (Figure 8) and the definition of a way of finding edges in the SI space are required. In this paper we propose finding the edges of a SI
following the same approach used with TI after a previous categorization of the continuous values of seismic traces that form the SI. Two different categorization approaches are shown. In the first approach, the categorization is carried out based on sorting out the large seismic amplitude values beyond one trace standard deviation (Figure 9). The large values (positive or negative) correspond to strong reflectors in the subsurface. The second approach categorizes the SI continuous variable considering values above or below a given percentile of seismic trace values (Figure 10).

6 Multidimensional Scaling

Multidimensional scaling (MDS) is a set of techniques use for exploring data similarities and dissimilarities. The approach used in this paper is the classic MDS also know as Torgerson Scaling or Torgerson-Gower Scaling, which takes as an input a matrix giving dissimilarities between pairs of high dimensional data (images) and outputs a coordinate matrix spatial representing points arranged in such a way that their Euclidean distance minimizes a loss function called strain (Borg, I. and Groenen, P., 1997). We use MDS in order to find the relationship in the TI and SI spaces separately and also between both spaces. The relationships are found visually on the 2D representation of the dissimilarity matrix. Figure 11 shows the 2D plot in which each point represents one of the 36 TIs used in this paper. The
figure is formed by clusters of three elements. These clusters are explained by the fact that the dissimilarity matrix used in this 2D MDS plot was computed using pixel-by-pixel distance, and under this condition changes on image resolution are not very relevant compared to changes in channel morphology, subsequently this cluster gather the same image at different resolutions.

**Figure 11**: MDS plot of TIs using pixel-by-pixel distance.

### 7 Uncertainties in the Original Space

Comparisons on how the different distances work in both spaces (TI and SI) are shown. This part is highly important since the capacity of the distances to capture the variability shown by the images is evaluated. Discussions on which type of distance are better for the purpose of evaluating the uncertainties in the TI to SI transform are present throughout this point.

#### 7.1 TI space

As it was mentioned before, three types of distances were used in comparing TIs and SIs. Figure 12 shows the MDS plot in the TI space obtained using different distances. The first two plots (Pixel-by-Pixel and Euclidean distance) show a systematic pattern in the point locations and also an easily noticeable presence of 3-elements clusters. These 3-element clusters are formed by TIs with the same channel features but at different resolution. Within the clusters every point representing an image resolution has a specific location relatively to the others two images at a different resolution. On the
other hand, the third plot (constructed using Haussdorf distance) does not show any systematic patterns between points. Due to this observation it might be possible that Hausdorff distance is not suitable for compare TIs with variations in resolution and channel morphology at the same time.

Figure 12: MDS TIs using different distances.

Figure 13 shows how the images are arranged in the plots constructed using Euclidean and pixel-by-pixel distances. Euclidean distance achieves a better distinction between images compared to pixel-by-pixel distance. The image clusters follow a clear column-wise correlation with respect to the TI matrix shown on the right (the colored arrows indicate that correlation). Pixel-by-pixel distance captures reasonably the image similarities in terms of channel widths, but they are not as well captured as when Euclidean distance is used. Moreover, the rectangles have an overlap, showing a flawed distinction between images based on the purposefully created varying morphologic features.

Figure 13: Relationship point location-channel profile.

Previously we mentioned that Hausdorff distance does not work well when different images and different resolutions are taken into account together. However, when no variations in resolution are
considered, this distance works much better (Figure 14). As described by Dubuisson and Jain (1994), the resolution changes affect largely the efficiency of Hausdorff distance in comparing images, but when these perturbations are larger than mere resolution changes, the results are fairly good. Another difference of Hausdorff distance with respect to the Euclidean and pixel-by-pixel distances happens in the way the data points are arranged. In this case they follow a row-wise correlation with respect to TI matrix (Figure 1). Depending on the resolution, the MDS 2D plots may look quite different. Nonetheless the correlation with respect to the TI matrix is always present.

![MDS TI-Hausdorff Distance](image1)

**Figure 14:** Hausdorff distance behavior for TIs considering images at the same resolution.

### 7.2 SI space

In the SI space Euclidean and pixel-by-pixel distances give a very similar configuration of points in the MDS 2D plots as is shown in Figure 15. Nonetheless, there is not an easy noticeable point distribution related to the SI matrix (Figure 6) as happened in the TI space, but a point structure is present as shown by Figure 20. The plot obtained using Hausdorff distance again does not give a systematic point configuration related to the SIs. Neither resolution nor shape changes are captured by using this distance. Euclidean and pixel-by-pixel distance behavior turn out to be almost equivalent given the similar pattern structure that they show.

![MDS SI distances](image2)

**Figure 15:** MDS of SIs using different distances.
Another way of computing distance between SIs proposed is considering the continuous SI variable, i.e., not performing a seismic trace amplitude categorization as was shown before. Figure 16 shows that using pixel-by-pixel distance on the continuous variable does not give good results, since there is no pattern of points related to the variations imposed on the TIs from which the SIs were obtained. On the other hand, Euclidean distance works very well in capturing TIs to SIs relationships. Moreover, applying this distance on the seismic trace continuous variable is equivalent to applying it on a categorical variable, giving the similarities in the point structure shown by the MDS 2D plots (Figure 17). Hence it would not be necessary to perform a categorization step in order to compare SIs in the SI space when Euclidean distance is used. Resolution changes affect the TI to SI transform very subtly, since the clusters are very compact.

Figure 16: MDS of SIs using continuous variables.

Figure 17: Correlation between categorical and continuous approach.

Figure 18 shows the effects on performing the SI categorization considering different extreme trace seismic values quantified using pixel-by-pixel distance. The thresholds are defined using the 10, 20, and
30 extreme percentiles (negative and positive values are considered separately). When a high threshold is used, the SIs tend to be more dissimilar, since the points increase their distances among each other. However, the point spatial configuration is practically the same for the different thresholds applied. Besides, four-points patterns are observed in all the plots. These patterns are related to the imposed column-wise morphological changes shown in the Figure 1, that is, decreases in channel widths.

Figure 18: MDS for different wavelet thresholds.

Figure 19 shows how the wavelet frequency affects the seismic forward modeling, and hence the patterns of points corresponding to the SIs. According to these plots, the larger the frequency range used the more apart the SIs are from each others (see plot on the right). However, every point conserves its relative position with respect the others. Moreover, in this case not only a column-wise but also a row-wise pattern correlation regarding the SI matrix is observed. As result, this parameter shows a very similar behavior to when the seismic trace threshold was varied (Figure 18). For a given TIs, increases in the frequency used in the seismic forward modeling produces SIs more different among themselves. This is explained by the fact that higher frequencies capture more of the geological features, generating more detailed SIs, with a greater chance of showing dissimilarities between them.

Figure 19: MDS of SI constructed using different wave frequencies.
8 Uncertainties in TI to SI Transform

Previously different distances were compared in order to find distances that capture the features shown by the different TIs and SIs used. Now we compare how the TI to SI transform works using these previously tested distances to build dissimilarity matrices and construct MDS 2D plots with them. Figure 20 shows the correlation between both spaces using Euclidean distance. As it was highlighted before, the TI space shows a clear column-wise correlation with respect to TI matrix showed in Figure 1. This pattern correlation is only partially observed in the SI space. This behaviour let us infer that well correlated images in one space may not necessarily generate images with the same correlation in the other space.

![Figure 20: Different spaces generated using Euclidean distance.](image)

Generally images close in one space tend to generate images close in the other space, although in the figure above the points which are not highlighted by a rectangle clearly do not to have a correlation as good in the SI space as in the TI space. Figure 21 shows how similarly correlated images in the TI space have different behaviours in the SI space. The images represented by points highlighted by a blue ellipse show very similar pattern distribution in both spaces, whereas the images mapped from one space to the other using coloured lines do not behave in the same way. In the TI space there is a clear three-element correlation, whereas in the SI these patterns are not observed.
9 Discussions and Future Work

Figure 22 shows how two far away pairs of images relative to the other points in the same plot (in this case images in the SI space) can be generated from two relatively much closer images in the other space. No matter the units on the axis in the plots, we would expect the braces in light blue and green to have similar dimension in both spaces, but this clearly does not happen in this case. This is an evidence of the non-uniqueness in the SI to TI transform. Due to this uncertainty, the task of inferring a TI model based on the seismic data available gets harder, since more than one set of features can generate very similar seismic responses. This turns out to be a serious drawback in the features interpretation from seismic data available.
It was shown how important it is to use a proper distance in order to quantify uncertainties in the TI to SI transform. As to the metric distances evaluated, Euclidean and pixel-by-pixel distances work equally well in capturing changes in the TI space not only in the channel morphology but also in the features scale representation, whereas Hausdorff distance is unstable when the features scale representation changes.

Performing an image categorization previously to compute distances in the SI space is a step that can be avoided by using Euclidean distance on the seismic trace amplitude taken as a continuous variable, since this distance generates equivalent results in the 2D MDS plots whether or not image categorization is carried out.

Exploring how sets of simulation obtained using MP geostatistic algorithms behaves in the TI to SI transform, new metric distances, and how changes in fluid saturation affects the TI to SI transform are possible extensions of this work.

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References


