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Modeling the Facies of Reservoir Using Seismic Data with Missing Attributes by Dissimilarity Based Classification

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ABSTRACT: Using seismic attributes as features for classification in feature space, in various aims such as seismic facies analysis, is conventional for the purpose of seismic interpretation. But sometimes seismic data may have no attributes or it is hard to define a small and relevant set of attributes in some applications. Therefore, employing techniques that perform facies modeling without using attributes is necessary. In this paper we present a new method for facies modeling of seismic data with missing attributes that called dissimilarity based classification. In this method, classification is based on dissimilarities and facies modeling will be done in dissimilarity space. In this space dissimilarities consider as new features instead of real features. A support vector machine as a powerful classifier was employed in both feature space (feature-based) and dissimilarity space (feature-less) for facies analysis. The proposed feature-less and feature-based classification is applied on a real seismic data from an Iranian oil field. Facies modeling using seismic attributes provide better results, but the feature-less classification outcome is also satisfactory and the facies correlation is acceptable. Indeed, the power of attributes to discriminate different facies causes to that facies analysis using attributes provide more reliable results comparing to feature-less facies analysis.

KEY WORDS: facies analysis, dissimilarity, feature, seismic attributes, classification, support vector-classifier.

0 INTRODUCTION

Seismic facies analysis is one of the important steps in seismic interpretation that is based on data classification through pattern recognition. Research in statistical pattern recognition has traditionally been dominated by feature vector approaches: objects are represented by feature sets of equal size. These are represented in vector spaces followed by the development of classifiers separating as effectively as possible the feature vector sets of different classes.

Almost the entire facies analysis is based on the seismic attribute, as a feature vector, and involves classification in feature space in which each dimension stands as a seismic attribute. Several studies for seismic facies analysis (SFA) have been proposed using seismic attributes (i.e., Paparozzi et al., 2011; Marroquín et al., 2009; Carrillat et al., 2008; Farzadi, 2006; Saggaf et al., 2003; Bhatt and Helle, 2002; West et al., 2002; Simaan, 1991; Dumay and Fournier, 1988; Mathieu and Rice, 1969). An important drawback of these approaches is that on a priori grounds attributes have to be defined that are strongly related with class differences. This set may not be too large both for computational reasons as well as to preserve the generalization power of the resulting classifiers. Feature spaces of increasing dimensionality finally deteriorate the recognition performance.

In this study we will reinvestigate the possibility of avoiding the necessity of finding attributes. We will return to one of the most naive approaches: distances or dissimilarities between direct sensor representations of the seismic samples. So we don't look for good attributes and we discuss the possibility to construct classifiers entirely in dissimilarity space, without a relation with the feature space. The classifier trained with complete objects in the dissimilarity space and applies this classifier to objects with missing data using the possibility to compute object dissimilarities even if objects are incompletely given. It aims to predict a label for every object according to the class that it belongs to, using a classification model that has been built from a training set. The labeled dataset (training) are collected from well logs using electro facies analysis (EFA) (Sutadiwirya et al., 2008) that in this method the logs are classified into a set of electro facies. The support vector classifier (SVC) is employed, as a powerful and flexible classifier, for both feature-based classification (in feature space) and feature-less classification (in dissimilarity space). Real data from an oil field in Iran are selected to examine our analysis.

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1 METHOD

1.1 Dissimilarity Based Classification

The feature-less classification method in dissimilarity space was first introduced by Duin et al. (1997). After that this method was improved by Pekalska and Duin (2005, 2002) and was used

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in various pattern recognition problems. Suppose that $d(\boldsymbol{y}_i,\boldsymbol{y}_j)$ is the dissimilarity value between the objects (seismic samples) $\boldsymbol{y}_i$ and $\boldsymbol{y}_j$, if i, j appertain to the same class the dissimilarity value is zero otherwise the dissimilarity amount is not zero and they belong to different classes. The dissimilarity of two seismic samples including P attributes (features) is computed as below

$$d(\boldsymbol{y}_i,\boldsymbol{y}_j)=\left(\sum_{q=1}^{p}\left|\boldsymbol{Y}_{iq}-\boldsymbol{Y}_{jq}\right|^2\right)^{\frac{1}{2}} \tag{1}$$

The variables $\boldsymbol{Y}_{iq}$ are the components of row vector $\boldsymbol{y}$. Assume R is a representation set (R: $\boldsymbol{y}_n$ and n=1, …, N), the dissimilarity vector of a new object $\boldsymbol{y}_r$ is calculated by Eq. (2).

$$\boldsymbol{d}=\left[d(\boldsymbol{y}_r,\boldsymbol{y}_1)d(\boldsymbol{y}_r,\boldsymbol{y}_2)...d(\boldsymbol{y}_r,\boldsymbol{y}_N)\right] \tag{2}$$

Each component of vector $\boldsymbol{d}$ is dissimilarity between object $\boldsymbol{y}_r$ and all objects of representation set. This vector is now considered as a new feature for dissimilarity based classification. For creating dissimilarity space, the dissimilarity matrix ($\boldsymbol{D}$) should be computed between all objects. Each column of matrix $\boldsymbol{D}$ is a dissimilarity vector and stand as a dimension of dissimilarity space.

As mentioned, the dissimilarity between the objects of the same class is small but between the objects of different class is large. According to this property, the same objects place close together in dissimilarity space but different objects split from each other. In other words, different classes separated and overlapping between them are reduced in dissimilarity space. Therefore, the discriminant boundary between different classes could be found more accurate (Duin et al., 2010; Pekalska and Duin, 2005, 2002).

1.2 Support Vector Classifier

The SVC is a powerful classification technique that proposed by Vapnik (1998) which has also been followed around the world. The optimization criterion here is the width of the margin between the classes. The concept of margin is the empty area around the decision boundary defined by the distance to the nearest training samples (Fig. 1). These samples, so-called support vectors, finally define the classification function (van der Heijden et al., 2004). Their number is minimized by maximizing the margin.

Suppose labeled objects (seismic samples) as $\boldsymbol{y}_1$, …, $\boldsymbol{y}_N$

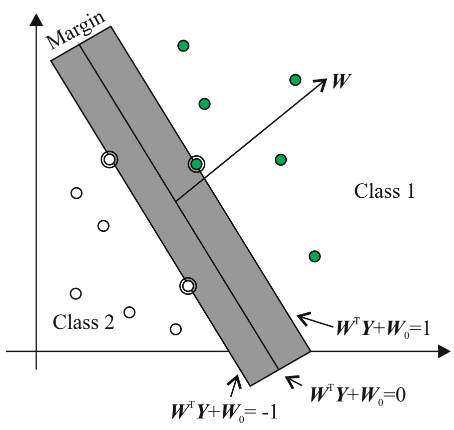

Figure 1. A schematic of support vector classifier.

with labels $\beta_n \in$ {-1, 1} for a two-class problem that the labels specify the class of each sample. A linear discriminant function is described as below

$$f(\boldsymbol{y})=\boldsymbol{W}^{\mathrm{T}}\boldsymbol{y}+\boldsymbol{W}_0 \tag{3}$$

That $\boldsymbol{W}$ is the gradient vector of $f(\boldsymbol{y})$. From Fig. 1, the value of this function is zero on separation boundary and

$$\boldsymbol{W}^{\mathrm{T}}\boldsymbol{y}_n+\boldsymbol{W}_0\le -1 \quad \text{for class 1 } (\beta_n=-1) \tag{4}$$

$$\boldsymbol{W}^{\mathrm{T}}\boldsymbol{y}_n+\boldsymbol{W}_0\ge -1 \quad \text{for class 2 } (\beta_n=+1) \tag{5}$$

The two above equations is summarized into below equation,

$$\beta_n(\boldsymbol{W}^{\mathrm{T}}\boldsymbol{y}_n+\boldsymbol{W}_0)\ge 1 \tag{6}$$

The margin amount is equal to $\frac{2}{\|\boldsymbol{W}\|}$. Therefore, to maximize the margin the value of $\|\boldsymbol{W}\|^2$ should be minimized

$$\|\boldsymbol{W}\|^2=\boldsymbol{W}^{\mathrm{T}}\boldsymbol{W} \tag{7}$$

The decision boundary should be as far away from the data of both classes as possible by maximizing the margin. An optimization approach for maximizing the margin and minimizing the distance is Lagrange multipliers, using that

$$L=\frac{1}{2}\|\boldsymbol{W}\|^2+\sum_{n=1}^{N}\alpha_n\left(\beta_n\left[\boldsymbol{W}^{\mathrm{T}}y_n+\boldsymbol{W}_0\right]-1\right), \quad \alpha_n\ge 0 \tag{8}$$

Variables $\boldsymbol{W}$ and $\boldsymbol{W}_0$ are two independent parameters that L should be minimized with respect to them and maximized with respect to α_n. After calculating the partial derivates of L with respect to $\boldsymbol{W}$ and $\boldsymbol{W}_0$ and setting them to zero, equations below are determined

$$\boldsymbol{W}=\sum_{n=1}^{N}\alpha_n\beta_n\boldsymbol{y}_n \tag{9}$$

$$\sum_{n=1}^{N}\beta_n\alpha_n=0$$

By using Eq. (9), Eq. (8) can transform to its dual-form

$$L=\sum_{n=1}^{N}\alpha_n-\frac{1}{2}\sum_{n=1}^{N}\sum_{m=1}^{N}\left(\beta_n\beta_m\alpha_n\alpha_m\boldsymbol{y}_n{}^{\mathrm{T}}\boldsymbol{y}_m\right), \quad \alpha_n\ge 0 \tag{10}$$

Now, we should maximize L with respect to α_n to compute and use them in Eq. (9) to find $\boldsymbol{W}$ and thereafter $f(\boldsymbol{y})$. Usually many of α_n have zero values and therefore have no role to find $\boldsymbol{W}$ and discriminant function. The samples $\boldsymbol{y}_n$ which their related α_n are not zero, they are called support vectors.

For non-linear separable data kernel method (Scholkopf et al., 1999) will be applied that it maps data into higher dimensional spaces to linearize the data in those dimensions. Thereafter it finds linear hyper plane there with maximum margin. This trick is used, because finding linear classifiers is much easier than non-linear ones (Vapnik, 1998). The important advantage of the SVC is that it offers a possibility to train generalizable, nonlinear classifiers in high-dimensional spaces using a small training set. Moreover, for large training sets, it typically selects a small support set which is necessary for designing the classifier, thereby minimizing the computational requirements during testing.

1.3 SVC in Dissimilarity Space

As mentioned above the dissimilarity space is created using dissimilarity vectors as new features, therefore SVC in dissimilarity space is introduced using dissimilarity vectors ($\boldsymbol{D}_{\Phi}$) instead of feature vectors ($\boldsymbol{y}$). Consider the labeled samples $\boldsymbol{y}_1, \ldots, \boldsymbol{y}_N$ as training set, the mapping operator related to object $\boldsymbol{y}$ is

$$\boldsymbol{D}_{\Phi} : \boldsymbol{y} \rightarrow \left[\boldsymbol{D}(\boldsymbol{y}_1, \boldsymbol{y}), \ldots, \boldsymbol{D}(\boldsymbol{y}_N, \boldsymbol{y})\right]^{\mathrm{T}} \tag{11}$$

From Eq. (11), each object $\boldsymbol{y}$ map to dissimilarity space by using $\boldsymbol{D}_{\Phi}$ which is a vector of distances between $\boldsymbol{y}$ and all N training set. Using the new features ($\boldsymbol{D}_{\Phi}$), a linear discriminant function in the dissimilarity space is defined as below

$$f(\boldsymbol{y}) = \boldsymbol{W}^{\mathrm{T}} \boldsymbol{D}_{\Phi}(\boldsymbol{y}) + \boldsymbol{W}_0 \tag{12}$$

Same as feature space the best discriminant function could be fined using support vector strategy by maximizing the margin. A nonlinear discriminant function in dissimilarity space could be obtained by using kernel trick same as feature space. In fact, dissimilarity vectors convert the original space to a higher-dimensional space and the relation between kernel ($\boldsymbol{K}$) and dissimilarities is defined as below

$$\boldsymbol{K}=\boldsymbol{D}\boldsymbol{D}^{\mathrm{T}} \tag{13}$$

2 APPLICATION

2.1 Real Data

A carbonate reservoir in Iran was processed to gain an insight into the feasibility of feature-less and feature-based facies analysis. Figure 2 shows a schematic cross-view of formations in this oil field. The lithology of the formation is heterogeneous and is divided into limestone, sandstone, dolomite, and shale as dominant lithologies which are reliably estimated from well logs and core data (Telmadarreie et al., 2012).

Seismic data in reservoir limits were cropped between time 2 000 to 2 200 ms including 10 wells (Fig. 3). The favorable lithofacies in this reservoir could be sandstone or limestone, sandstone is highly porous facies with proper pore structure type and limestone is a facies with high fracture density. Finding these facies using a reliable lithofacies analysis helps us to define the reservoir zone accurately. Figure 4 shows the seismic data at time slice (a horizontal display) 2 076 ms of 3D data.

For collecting data labeled as training dataset, the label codes are needed from facies log which can be obtained through electro facies analysis. EFA was performed using the logs neutron porosity (NPHI), bulk density (RHOB), sonic log (DT) and gamma ray (GR) to obtain facies logs. EFA is based on the multi-resolution graph based clustering (MRGC) as a subset of heretical clustering methods that analyzes the well logs to identify different groups of electro facies (Sutadiwirya et al., 2008). From the results, each facies log contains dominant lithology including dolomite, limestone, sandstone, and shale.

An optimal training dataset should cover homogenously the whole seismic cube. Therefore, 7 wells were selected for collecting training data set, and 3 wells (wells MN-282, MN-283, and MN-343) remained hidden to verify the resulted facies analysis using feature-less classification and feature-based classification. For validation of both approaches, the SFA results are compared to the known facies present at hidden wells.

2.2 Facies Analysis Using Attributes (Feature-Based)

Seismic attributes quantify specific data characteristics, and so represent subsets of the total information. Generally, the definition of seismic attributes includes all quantities derived from seismic data that can provide some qualitative information about the physical parameters of the carbonate reservoirs. Facies analysis performs through the pattern recognition that seismic attributes are used as effective discriminators for the purpose of facies classification.

In this step, we first extracted 14 attributes containing: apparent polarity, attenuation, cosine of phase, dominant frequency, envelope, first derivative of envelope, instant frequency, instant

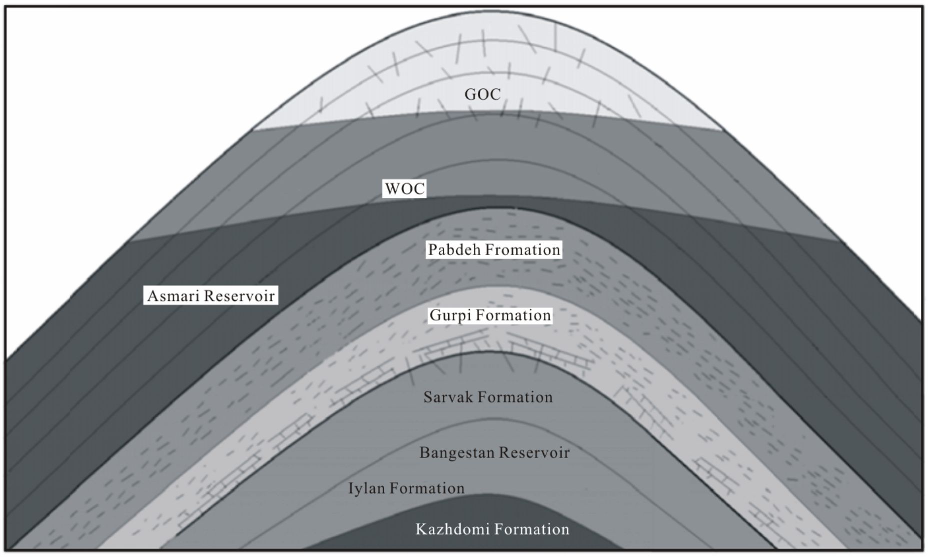

Figure 2. A schematic cross-view of carbonate reservoir case of study.

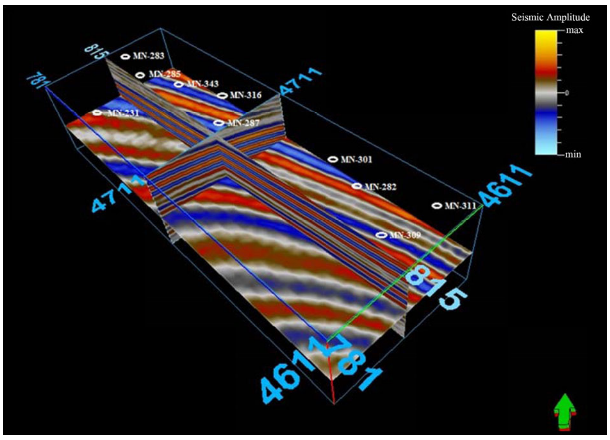

Figure 3. The seismic data in reservoir boundary including 10 wells.

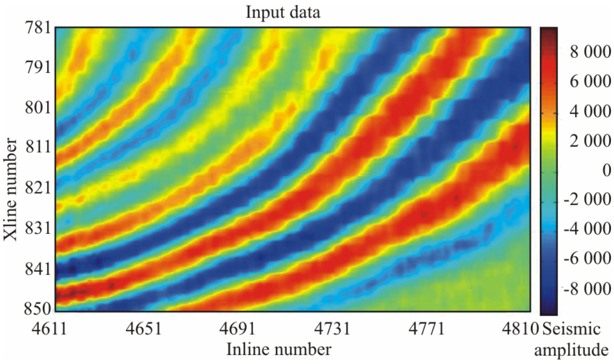

Figure 4. Seismic data at time slice (a horizontal display) 2 076 ms of 3D data.

phase, is frequency, quadratic amplitude, reflection intensity, relative acoustic impedance (RAI), root mean square (RMS) amplitude, and second derivative of envelope. It is worth noting that some of these attributes are redundant and add to complexity of feature space, thus a set of appropriate attributes must be chosen. We concluded that the best attributes for SFA in this problem are cosine of phase, envelope, RAI, and is frequency (Bagheri and Riahi, 2014; Bagheri et al., 2013).

A cross plot of two selected attributes (RAI and envelope) shown in Fig. 5 implies that choosing suitable attributes successfully separate samples. According to this plot, it's clear that each class (facies) discriminates effectively using these attributes and simplifies the lithofacies classification. Thus, classification of different facies using these attributes makes it more sensible and easier.

The next step is building a powerful classifier that need training set (labeled samples) which is collected through EFA. For creating a classifier, labeled data set is divided into training and testing set. Next, SVC is trained in feature space using training set and classifier is validated using testing set through calculating their mean square error (MSE) criterion. To do this, 70% of representation set was selected as a training set and 30% as a testing set for calculating MSE. The resulting MSE related to feature-based facies analysis obtained 10.05% that is relatively low.

After retrieving discriminant functions associated with SVC corresponding to lowest MSE, we mapped it on unlabeled

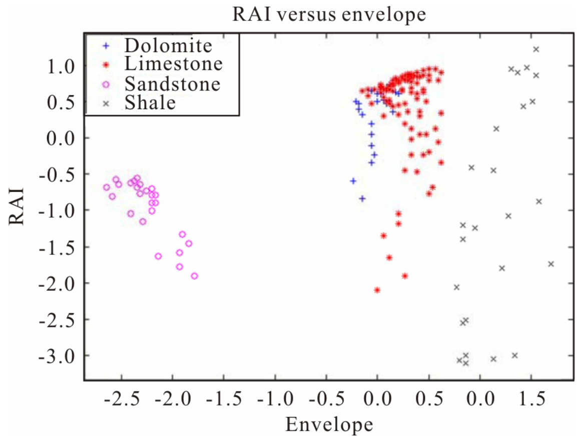

Figure 5. Cross plot of RAI and envelope. Different facies discriminated using these attributes.

samples to obtain the spatial distribution of the reservoir facies. The result of feature-based facies analysis using SVC is shown in Fig. 6. In order to validate feature-based classification, we calculated the facies correlation in each hidden well, MN-282, MN-283, and MN-343, from the estimated and observed facies. The average facies correlation in 3 wells obtained 44% which show high level of validation and correlation coefficient in this case. It is because of the ability of seismic attributes to discriminate different facies in feature space.

2.3 Facies Analysis without Using Attributes (Feature-Less)

The main problem of feature-based facies analysis is that on a priori grounds, seismic attributes have to be defined that are strongly related with class differences. The attribute set may not be too large both for computational reasons as well as to preserve the generalization power of the resulting classifiers. Feature spaces of increasing dimensionality finally deteriorate the recognition performance. In this section we try to perform feature-less facies analysis in dissimilarity space that is created without using attributes. In dissimilarity space dissimilarities are considered as new features instead of seismic attributes.

The procedure of building a classifier in dissimilarity space is same as feature space that is mentioned above. The classifier trained with labeled objects in the dissimilarity space and applies this classifier on unlabeled object to specify its class that it belongs to. The average resulting MSE related to feature-less classification, during building classifier, is obtained as 21.83%, which is not low.

Same as feature-based classification, after retrieving discriminant functions associated with SVC corresponding to its lowest MSE, we mapped it on unlabeled samples to obtain facies model. The result of feature-less facies analysis using SVC is shown in Fig. 7. In order to validate feature-less classification, we calculated the average facies correlation in tree hidden wells from the estimated and observed facies. The average facies correlation is obtained 19.33% which show low level of validation and correlation coefficient.

From the results, the feature-based classification shows more performance comparing to feature-less classification in facies analysis. The main reason of this result is related to overlapping samples of different facies in dissimilarity space. In other

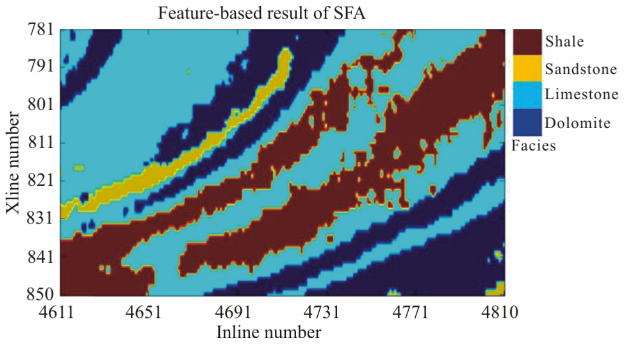

Figure 6. Feature-based resulted seismic facies using SVC at time slice 2 076 ms in feature space.

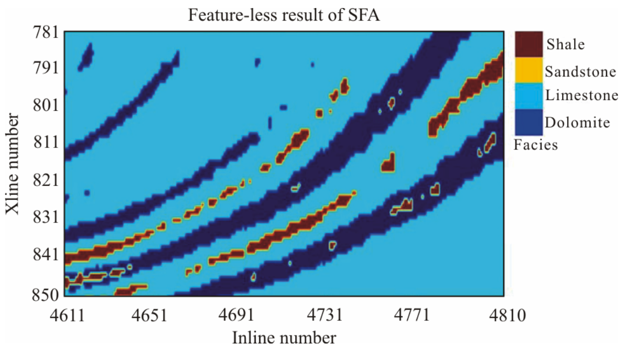

Figure 7. Feature-less resulted seismic facies using SVC at time slice 2 076 ms in dissimilarity space.

words not using seismic attributes, as discriminators, causes the overlapping of different facies samples and non-separable data.

3 CONCLUSIONS

The main goal of this study is to argue and illustrate that it is feasible to build classifiers on object dissimilarities for the purpose of seismic facies analysis. This opens a new type of applications in which feature representations are replaced by distance measures. At the cost of large learning sets and complicated learning systems, discriminant functions have to be found. Object based discriminant analysis will be of importance in applications where no natural discriminative features are given, but instead some object similarity measure can be supplied. One of the most promising aspects of object based discriminant analysis is that it removes the need for small sets of good features in case of small training sets.

The power of SVC is to find an accurate discriminator boundary, because of its ability to train nonlinear classifiers in high-dimensional spaces using a small training set. This characteristic of SVC is the reason we employed this classifier for facies analysis. This classifier is applied in feature space and dissimilarity space to evaluate feature-based and feature-less classification performance for facies analysis. The higher performance of feature-based facies analysis compared to feature-less is investigated in two steps. First, the misclassification error using feature-based classification is less than feature-less classification. Second, the high level of facies correlation in hidden well susing seismic attributes in feature space compared to feature-less (dissimilarity based) classification. These two validation steps demonstrate the ability of seismic attributes for facies analysis. Generally, the lack of attributes generates statistical-variations in the data and consequent deterioration in the classification model and, as a result, classification accuracy is reduced.

Regardless of the mathematical algorithm, facies correlation and reliability of facies analysis depend on the quality of data. Usually, various steps of seismic processing such as filtering, stacking and migration disturb or destroy trace amplitudes. This deficiency causes reduced facies correlation and accuracy of facies analysis.

Finally it should be noted that, although feature-based classification shows better performance compared to feature-less classification in facies analysis, it couldn't be applied to a problem with missing attributes. On the other hand, feature-less classification is more computationally efficient and it is able to give us a general view of the reservoir facies distribution in a short time.

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