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# Support Vector Machine-based Facies Classification Using Seismic Attributes in an Oil Field of Iran

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## Abstract

Seismic facies analysis (SFA) aims to classify similar seismic traces based on amplitude, phase, frequency, and other seismic attributes. SFA has proven useful in interpreting seismic data, allowing significant information on subsurface geological structures to be extracted. While facies analysis has been widely investigated through unsupervised-classification-based studies, there are few cases associated with supervised classification methods. In this study, we follow supervised classification scheme under classifiers, the support vector classifier (SVC), and multilayer perceptrons (MLP) to provide an opportunity for directly assessing the feasibility of different classifiers. Before choosing classifier, we evaluate extracted seismic attributes using forward feature selection (FFS) and backward feature selection (BFS) methods for logical SFA. The analyses are examined with data from an oil field in Iran, and the results are discussed in detail. The numerical relative errors associated with these two classifiers as a proxy for the robustness of SFA confirm reliable interpretations. The higher performance of SVC comparing to MLP classifier for SFA is proved in two validation steps. The results also demonstrate the power and flexibility of SVC compared with MLP for SFA.

**Keywords:** Seismic Facies, Support Vector Machine, Multilayer Perceptrons, Seismic Attributes, Classification.

## 1. Introduction

SFA has proven useful in interpreting seismic data and can extract useful information on lithology variations and the structure of reservoirs to find the best trap location and decrease the risk of drilling. Pattern recognition algorithms have been extensively used to incorporate seismic data into lithology estimation. For example, Mathieu and Rice (1969) employed a discriminant-factor analysis to interpret lithologic changes in a reservoir from seismic data; Dumay and Fournier (1988) employed both the principal component analysis (PCA) and the discriminant factor analysis to recognize the seismic facies. Simaan (1991) improved a knowledge-based expert system to segment the seismic section based on its texture. Saggaf et al. (2003) used a competitive neural network to detect seismic facies. Farzadi (2006) employed hierarchical clustering method and seismic attributes for SFA. Recently, Marroquin et al. (2009) prepared a visual data-mining methodology for SFA. In addition, Paparozzi et al. (2011) proposed the probabilistic classification of reservoir facies for static reservoir modeling. Supervised machine learning is the search for algorithms that come from externally supplied instances to produce general hypotheses, which then make predictions about future instances. In other words,

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the goal of supervised learning is to build a concise model of the distribution of class labels in terms of predictor features (Kotsiantis, 2007). In such a learning system, training set as a labeled dataset is used to build a classifier. The training dataset are collected from well logs using electro facies analysis (EFA) (Sutadiwirya et al., 2008). Next, the trained classifier is mapped to unlabeled data to label and classify them to different classes. While SFA has been widely investigated through unsupervised-classification-based studies, there are few cases associated with supervised classification methods.

The classification of seismic data using a linear classifier is not simply possible, reflecting the fact that they have high overlapping in feature space. Therefore, depending on the manner in which these problems are posed, we must focus on powerful nonlinear classifiers to find nonlinear discriminant function between classes. In this study, we follow supervised classification scheme under two classifiers, namely the SVC and MLP, to provide an opportunity for directly assessing the feasibility of different classifiers.

Feature, called attribute, selection is one of the most important steps in pattern recognition. Therefore, it needs to evaluate the extracted seismic attributes using FFS and BFS methods to select relevant attributes for making feature space (Hashemi and Javaherian, 2009). Facies obtained from seismic data depend on properties such as amplitude, frequency, and phase of signals to be considered in attribute selection.

A data from an oil field in Iran are selected to examine our analysis. The results are discussed and the best output is selected for seismic facies and geological modeling in reservoir limits.

## 2. Theory description

A lot of earlier studies for SFA come from various techniques of artificial neural network (e.g. Saggaf et al., 2003; Aminzadeh and de Groot, 2006). Herein, we analyze 2 classifiers, namely the SVC and MLP, to evaluate the aspects of different classifiers.

### 2.1. Support vector classifier

The SVC is a powerful classification technique 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, i.e., the empty area around the decision boundary defined by the distance to the nearest training patterns. These patterns, so-called support vectors, finally define the classification function (Van der Heijden et al., 2004). Their number is minimized by maximizing the margin.

Assume, we have training samples $X_n$, n=1,…, $N_s$ and there is a label for each sample ($C_n \in \{-1,1\}$), indicating to which of the two classes the sample belongs. Then, a linear classifier function is defined as follows:

$$f(x) = W^T x + b \tag{1}$$

where,

$$W^T x_n + b \geq 1 \quad if \quad c_n = +1 \quad for\ all\ n \tag{2}$$

$$W^T x_n + b \leq 1 \quad if \quad c_n = -1 \quad for\ all\ n \tag{3}$$

These two constraints can be rewritten into one inequality as reads:

$$c_n (W^T x_n + b) \geq 1 \tag{4}$$

The gradient vector of *f*(x) is W. Therefore, the square of the margin is inversely proportional to:

$$||W||^2 = W^T W \tag{5}$$

To maximize the margin, we have to minimize $||W||^2$.

Using Lagrange multipliers; we can incorporate the constraints (4) into the minimization:

$$L = \frac{1}{2} ||W||^2 + \sum_{n=1}^{N_s} \alpha_n (c_n [W^T x_n + b] - 1), \ \alpha_n \geq 0 \tag{6}$$

L should be minimized with respect to W and b, and maximized with respect to the Lagrange multipliers αn. Setting the partial derivatives of L w.r.t. w and b to zero results in the constraints:

$$W = \sum_{n=1}^{N_s} \alpha_n c_n \, x_n \quad (7)$$

$$\sum_{n=1}^{N_s} c_n \alpha_n \ = 0$$

Reconstituting this into (6) gives the so-called dual form:

$$L = \sum_{n=1}^{N_s} \alpha_n - \frac{1}{2} \sum_{n=1}^{N_s} \sum_{m=1}^{N_s} (c_n c_m \alpha_n \alpha_m {x_n}^T x_m) \, , \alpha_n \ \geq \ 0 \quad (8)$$

L should be maximized with respect to the $\alpha_n$. After optimization, the $\alpha_n$ are used in (7) to find W. In typical problems, the solution is sparse, meaning that many of the $\alpha_n$ become 0. Samples ($x_n$) for which $\alpha_n = 0$ are not required in the computation of W. The remaining samples $x_n$ (for which $\alpha_n > 0$) are called support vectors.

For non-linear separable data, kernel method (Scholkopf et al., 1999) will be applied to the maximum margin hyper plane. This transforms data to a higher dimensional space and finds linear hyper plane there, while in original data space a non-linear margin will be constructed (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.

## 2.2. MLP classifiers

MLP represents the most prominent and well-researched class of ANN's in classification. MLP consists of several layers of nodes interconnected through weighted acyclic arcs from each preceding layer to the following without lateral or feedback connections Each node calculates a transformed weighted linear combination of its inputs with the vector of output activations from the preceding layer. The column vector of weights and a bounded non-decreasing non-linear function (e.g., the linear threshold or the sigmoid) with one of the weights act as a trainable bias connected to a constant input.

For pattern classification, MLP adapts the free parameter through supervised training to partition the input space through linear hyper planes. The driving force of the training procedure is, however, the minimization of a criterion such as the apparent classification error or the mean square error (MSE) between the classifier output and some preset target values.

It is important to note that neural networks can lead to many different classifiers depending on how they are trained (Jain et al., 2000). While the hidden layers in MLP allow nonlinear decision boundaries, they also increase the danger of overtraining the classifier, the main defect of MLP, since the number of network parameters increases as more layers and more neurons per layer are added. Therefore, the regularization of neural networks may be necessary.

## 3. Real example application

A 3D seismic data from an oil field in Iran was processed to gain an insight into the feasibility of using different classifiers in the supervised classification scheme. 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. The formation is divided into seven zones, namely A1, A2, A3, A4, A5, A6, and A7, among which the A6 is the sandstone reservoir zone. The location of oil field is shown in Figure 1.

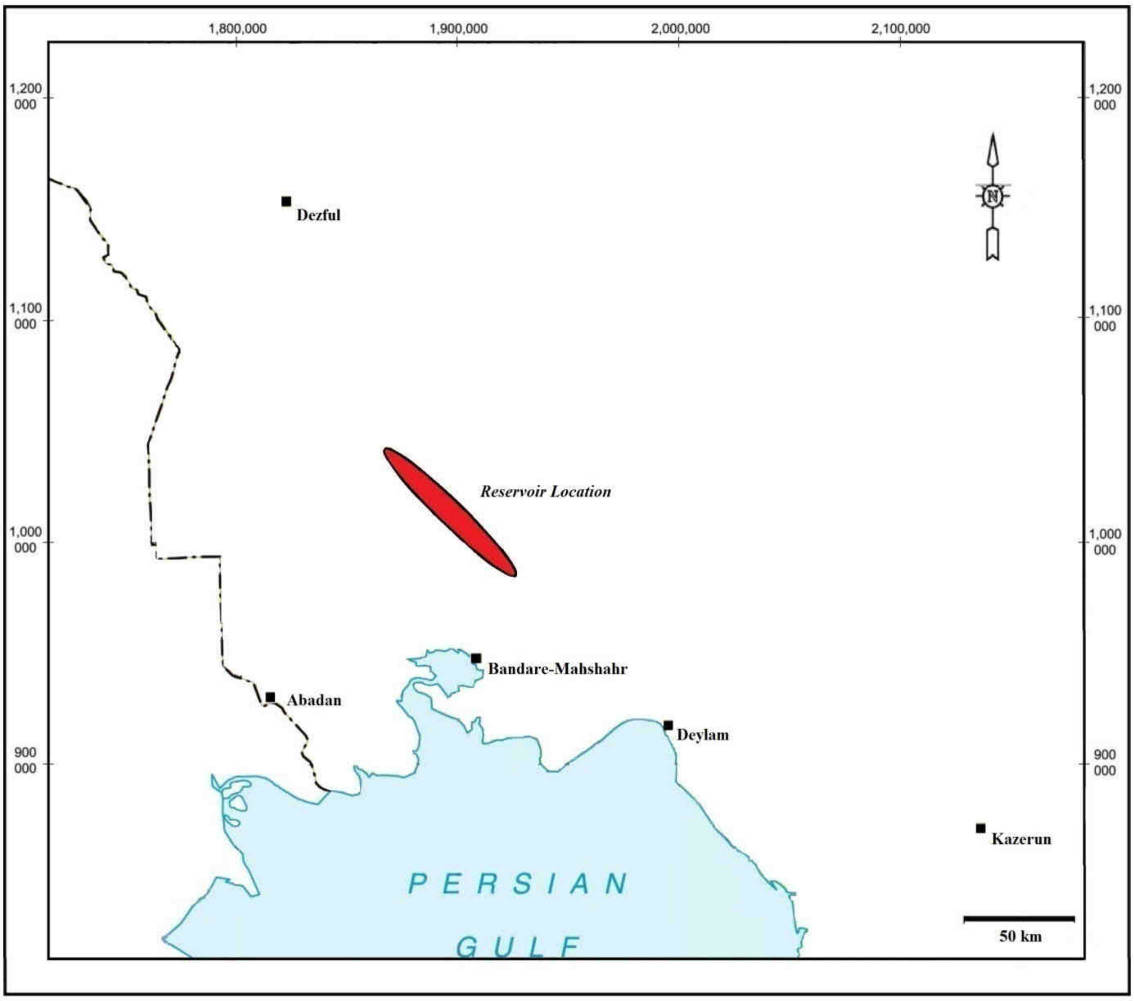


**Figure 1**
Map of selected oil field (N.I.O.C.)

Seismic data in reservoir limits were cropped between the time period of 2000 ms to 2200 ms including 10 wells (Figure 2). The favorable lithofacies in this reservoir is sandstone, which is a highly porous facies with proper pore structure type and oil as fluid content. Finding this facies using a reliable lithofacies analysis helps us to define the reservoir zone accurately. The processing is carried out in the steps which are briefly described here.

## 3.1. Dataset

For collecting labeled data as training dataset, the label codes are needed which can be obtained through electro facies analysis. EFA was performed using the logs NPHI, RHOB, DT, and GR (Figure 3a) and the core data were used as the guidance data.

The classification method for EFA is based on the multi-resolution graph based clustering (MRGC). This method analyzes the underlying data structure to define natural groups of electro facies (clusters). As shown in Figure 3b, each facies log contains dominant lithology including dolomite, limestone, sandstone, and shale which are known as lithofacies.

For mining training dataset, we considered 50 meters around wells as a homogeneous area to use facies logs for labeling seismic traces in this homogeneous area. Well locations and seismic survey area are shown in Figure 4. 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 for the validation of supervised classification using different classifiers. For the validation of each classifier, the SFA result of each classifier is compared to the known facies present at hidden wells.

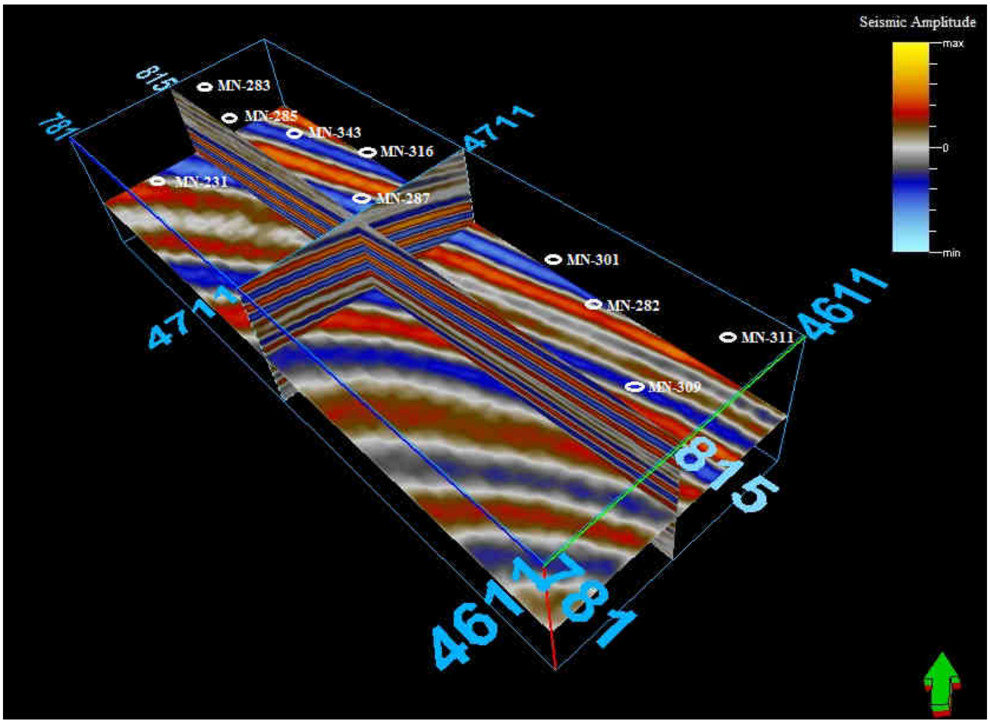


**Figure 2**
3D seismic data in reservoir limits, selected from an oil field of Iran

## 3.2. Attribute selection

Seismic attributes describe seismic data. They quantify specific data characteristics and thus represent the subsets of the total information. In effect, attribute computations decompose seismic data into constituent attributes. In the second step, first 14 attributes, namely apparent polarity, attenuation, cosine of phase, dominant frequency, envelope, first derivative, instant frequency, instant phase, ISO frequency, quadratic amplitude, reflection intensity, relative acoustic impedance, RMS amplitude, and second derivative were extracted. It is worth noting that some of these attributes are redundant and add to the complexity of feature space. Therefore, the best attributes must be selected. For attribute selection, FFS and BFS methods were used to evaluate attributes. In addition, covariance matrix for all the attributes was calculated. With analyzing this matrix, we concluded that the best attributes for SFA in this problem, mainly due to low correlation between them, were cosine of phase, envelope, ISO frequency, and relative acoustic impedance (RAI). On the other hand, cosine of phase, envelope and ISO frequency were related to the variation of phase, amplitude, and the frequency of signal respectively. Their variations show changes in signal shape, which is considered an important factor for seismic facies analysis. Additionally, RAI was related to changing lithology, which played a significant role in lithofacies analysis; hence these 4 attributes were selected as the best attributes.

The scatter plot of the selected attributes (cosine of phase, envelope, ISO frequency, and RAI) shown in Figure 5 implies that choosing suitable attributes successfully separates samples. If the cross plots of the attributes are observed pair by pair in detail, i.e. cosine of phase and envelope, each class discriminates effectively using these attributes and simplifies the lithofacies classification. Thus, the classification of different facies using these attributes makes more sense and is easier.

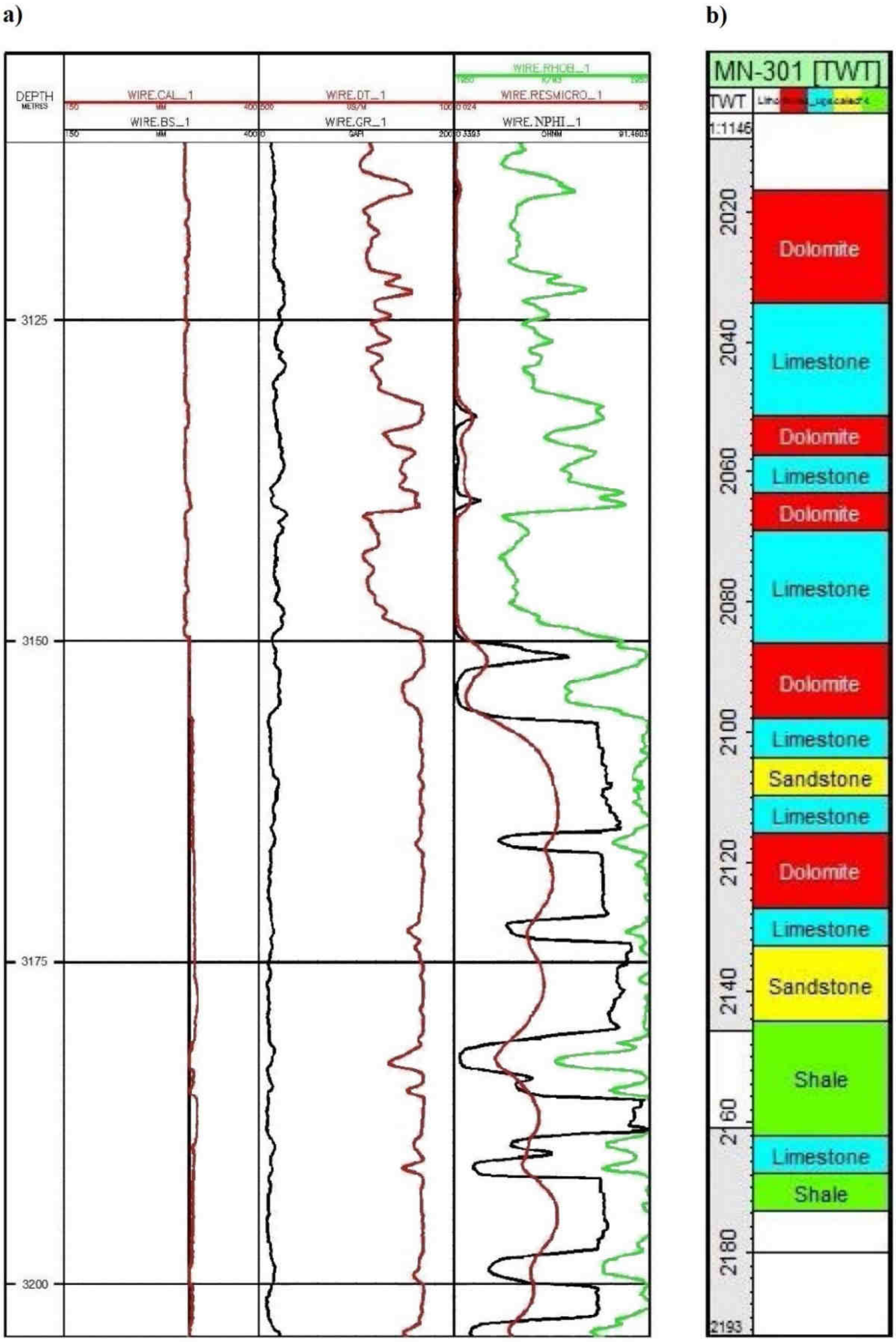


**Figure 3**

(a) NPHI, RHOB, DT, and GR selected logs for EFA; (b) one of the obtained facies log using MRGC. Lithofacies are dolomite, limestone, sandstone, and shale.

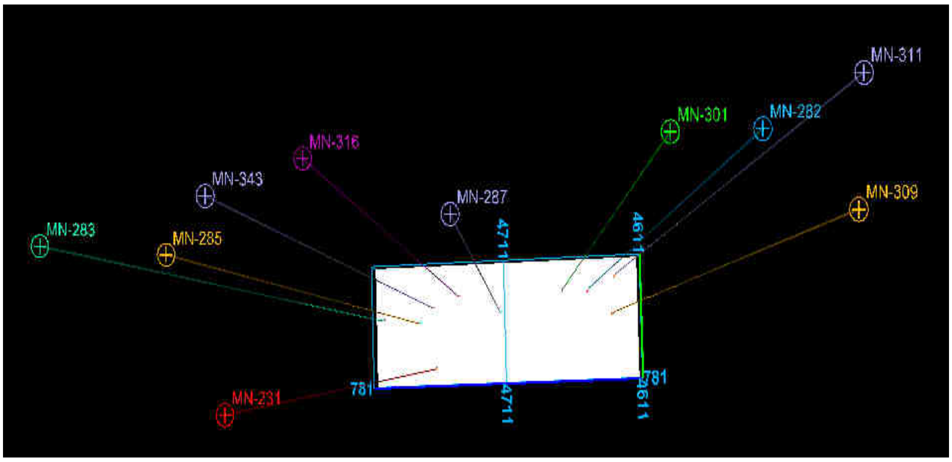


**Figure 4**
Ten facies logs position in this survey area; wells MN-282, 283, 343 are hidden for the validation of SFA analysis.

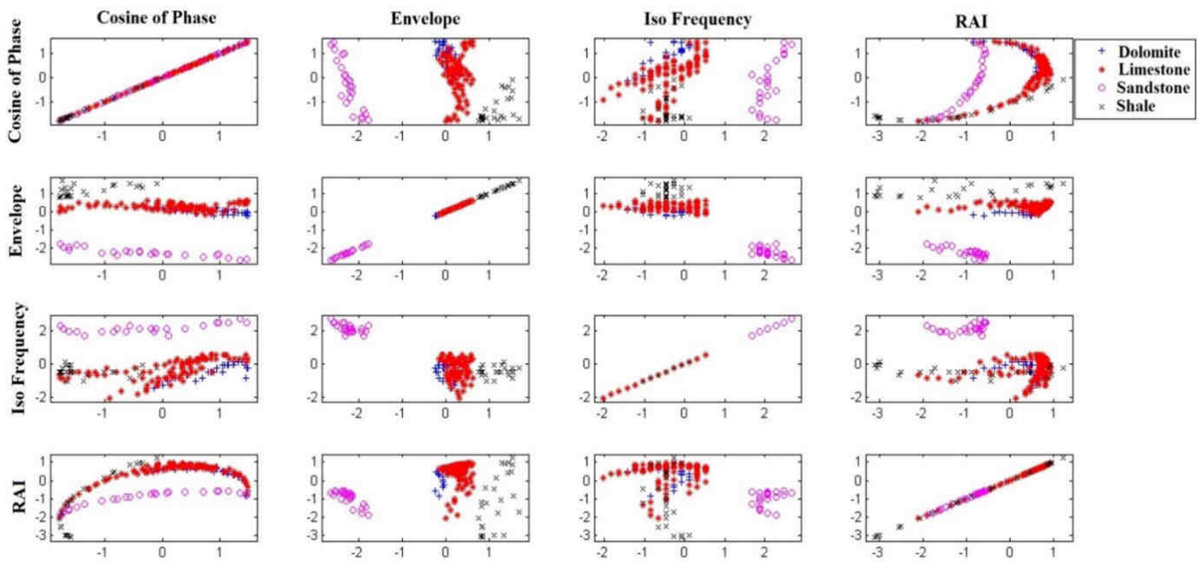


**Figure 5**
Scatter plot of four selected attributes pair by pair; x and y axis are different attributes.

### 3.3. Building SVC and MLP classifiers

After collecting labeled data as a representation set and extracting best attributes, labeled data set was divided into training and testing set. Next, SVC and MLP classifiers were trained in feature space using training set; each dimension of feature space was an attribute and classifier was validated using testing set through calculating their MSE criterion.

For comparing SVC and MLP classifiers, the representation set size was changed in the implementation of them, the case that 70 percent of representation set were selected as a training set and 30 percent as a testing set for calculating MSE. The average MSE was computed over 30 repetitions using a cross-validation technique. The results indicated a low level of misclassification error corresponding to SVC comparing to MLP (Figure 6), implying that SVC was more reliable and reflecting its efficiency compared to MLP. This was because of the ability of SVC to train generalizable, nonlinear classifiers in high-dimensional spaces using a small training set.

After retrieving discriminant functions associated with SVC and MLP classifiers, they were mapped onto unlabeled data. The results of facies analysis using SVC and MLP are shown in Figure 7a and Figure 7b respectively. In order to re-validate different classifiers, the facies correlation in each hidden well, namely MN-282, MN-283, and MN-343, was calculated from the estimated and observed facies. The results showed 64.66% facies correlation using SVC and 58% facies correlation using MLP classifier. It is obvious from the results that SVC with a high level of validation and correlation coefficient in each well is better suited in supervised classification scheme compared to MLP. It is because of the ability of SVC to train generalizable, nonlinear classifiers in high-dimensional spaces using a small training set. These observations also support the suggestion of reliability of SVC made in this study.

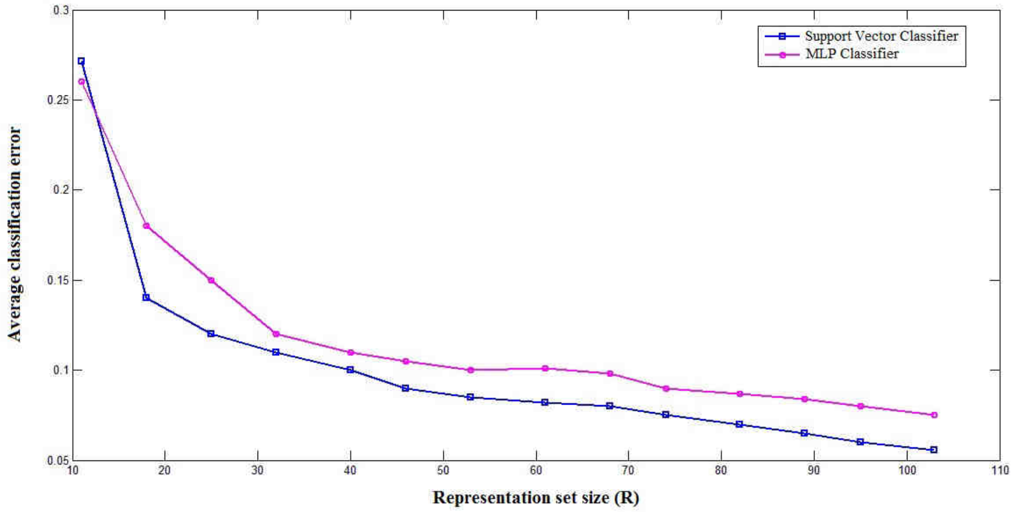


**Figure 6**
Comparison of the performance of SVC and MLP classifiers; the average classification error using SVC is less than MLP classifiers; therefore, SVC is more reliable compared to MLP.

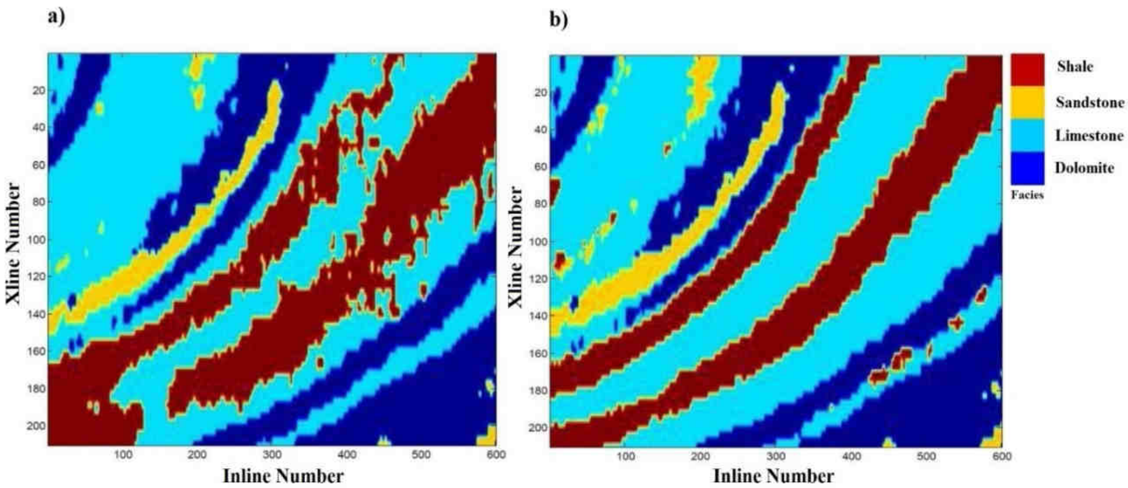


**Figure7**
Results of SFA using SVC and MLP at a time slice of 2076 ms of seismic data. The results show 64.66% facies correlation using SVC (a) and 58% facies correlation using MLP classifier (b). The high facies correlation (64.66%) in hidden wells location proves the reliability of SFA using SVC. The location of sandstone as favorable lithofacies, highly porous facies with a proper pore structure type and oil as fluid content is resulted using SVC reliably (yellow color).

## 4. Conclusions

In this study, SVC and MLP classifiers were employed for the supervised classification scheme to evaluate their performance in facies analysis. The supervised classification scheme for SFA is based on well logs to obtain facies logs using EFA, to collect training dataset as labeled data, and to build and train a classifier.

Separating seismic data using a linear classifier is a crucial problem, reflecting the fact that they have high overlapping in feature space. Therefore, depending on the manner in which this problem is posed, we must focus on powerful nonlinear classifiers to find nonlinear discriminant function between classes. The ability of SVC to find discriminator boundary and separating different classes is better compared to MLP, which is because of the important advantage of its possibility to train generalizable, nonlinear classifiers in high-dimensional spaces using a small training set. This ability yields a high performance of SVC for the classification of complicated data such as seismic data. The high performance of SVC compared to MLP is clarified in two steps. First, the cross plot of misclassification error versus representation set size shows that the MSE using SVC is less than MLP. Second, in hidden wells, the SFA using SVC has a high level of facies correlation. These two steps validation demonstrate the power and flexibility of SVC compared to MLP.

The resulted SFA using SVC corroborates our existing understanding of the reservoir and shows substantial similarity to previous studies. Using reliable SFA by SVC method, sandstone was found to be a favorable lithofacies, the best trap location, a highly porous facies with proper pore structure type, and with oil as fluid content (yellow color). Based on this achievement, the risk of drilling production wells decreases in sandstone facies area (yellow color).


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### Nomenclature

| | |
|---|---|
| SFA | : Seismic facies analysis |
| SVC | : Support vector classifier |
| MLP | : Multilayer perceptrons |
| FFS | : Forward feature selection |
| BFS | : Backward feature selection |
| EFA | : Electro facies analysis |
| ANN | : Artificial neural network |
| MSE | : Mean squared error |
| NPHI | : Neutron porosity log |
| RHOB | : Bulk density log |
| DT | : Sonic log |
| GR | : Gamma ray log |
| MRGC | : Multi-resolution graph based clustering |
| RAI | : Relative acoustic impedance |
| NIOC | : National Iranian Oil Company |

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