Multiattributes pattern recognition for reservoir prediction

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Summary

A new classification technique is presented to recognize and predict reservoirs from seismic data using support vector machine (SVM) pattern recognition. As the method is data-driven it is especially suitable for use with non-linear multiattributes. The method has good generalization ability for cases where the populations are small. In this paper, we describe the method, and apply the method to a 3D seismic dataset for the "Large Save" oilfield. First, we train the SVM using 3D seismic multiattributes at known well locations with well test results. The resulting SVM structure is used to make predictions away from the wells. It is demonstrated that the method is less subject to overtraining difficulties and can be used to distinguish oil and gas reservoirs.

Introduction

Pre-drill prediction of the occurrence of reservoir is an important step in seismic exploration and development. Recently, geostatistics and neural networks have been used to predict well log properties from combinations of various seismic attributes. Known well to seismic ties are used to learn the relationship between the seismic data and the well values. However, for small populations (ie., only a few well-seismic attribute pairs), statistical significance may be impossible to achieve and neural network can be easily "overtrained" which results in "overfitting" and poor predictions in validation trials. We present a new approach, suitable for small samples having good generalization ability, called Support Vector Machine (SVM) pattern recognition. In the paper we applied SVM to a 3D seismic data volume for reservoir prediction.

SVM is a type of pattern classifier based on a novel statistical learning theory that has been recently proposed by Vapnik (1998) and other researchers. Unlike traditional methods (e.g. neural networks), which minimize the empirical, training error, SVM aims at minimizing an upper bound of the generalization error through maximizing the margin between the separating hyperplane and the data. SVM is known to generalize well even in high dimensional spaces under the empirical risk minimization principle employed by most of neural networks and has been successfully applied in a variety of ways ranging from face detection, verification, and recognition, object detection and recognition, handwritten character and text recognition, speech and speaker verification etc. The algorithm has also been used in geophysical data processing and inversion (Li and Castagna, 2004; Kuzma, 2003).

Principle of SVM pattern recognition

For pattern recognition based on statistical learning theory, we try to estimate a function $f \rightarrow \{+1,-1\}$ using input-output training data

$$(\mathbf{x}_1, y_1), \cdots\cdots, (\mathbf{x}_l, y_l) \qquad (1)$$

such that f will correctly classify unseen examples $(\mathbf{x}, y)$ that were generalized from the same underlying probability distribution $P(\mathbf{x}, y)$ as the training data. The simplest case is linear data separable by a hyperplane without errors. But in the case where the training data cannot be separated by a hyperplane without errors, our goal is to construct the hyperplane that makes the smallest number of errors.

The generalization ability of the learning machine is based on the factors described in the theory for controlling the generalization ability of the learning processes. The bound controlling this can be written in the form

$$R(\alpha) \le R_{emp}(\alpha) + \Phi(h) \qquad (2)$$

Here, $R(\alpha)$ is the bound;

α is an index for the bound;

R_{emp} is the empirical risk function;

$\Phi(h)$ is the confidence interval;

h is the number of dimensions of machine structure.

There are two constructive approaches to minimizing the right-hand side of the inequality. Neural Networks minimize the first term that easily produces “overfitting”. Support Vector Machine, to avoid overfitting, keeps the value of the empirical risk fixed and minimizes the confidence interval. It is quite possible that by minimizing this ratio one can control the generalization better than by maximizing the margin (which is inverted to the empirical risk).

The SVM uses local risk minimization approach that has an advantage when on the basis of the given structure on the set of a function it is impossible to approximate well the desired function using a given number of observations. However, it may be possible to provide a reasonable local approximation to the desired function at any point of interest.

The special advantage of the Support Vector Machine is that it can work for the non-separable data case (Vapnik, 1998). In order to achieve this, the SVM maps the input data into a high dimensional feature space. A construction of the linear separation hyperplane is done in this high dimensional feature space

$$(\boldsymbol{\omega} \cdot \mathbf{x}) - b = 0$$

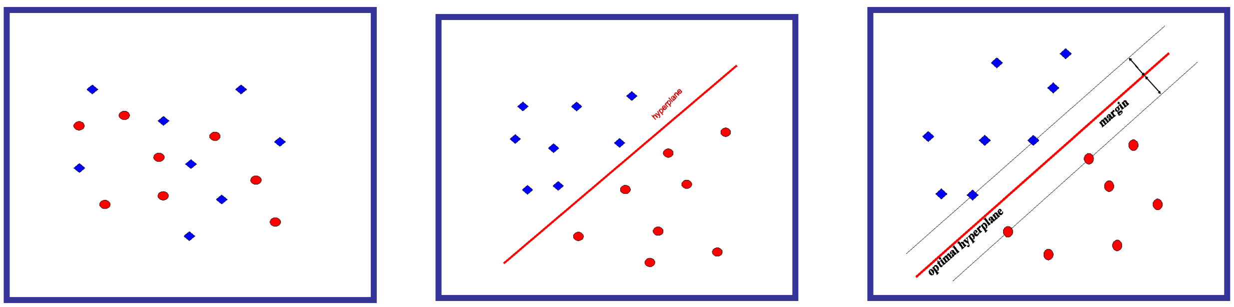

Figure 1: hyperplane: data, hyperplane, margin and support vector in the feature space. It maximizes the distance between the nearest point and hyperplane.

The solution to this optimization problem is given by the saddle point of the Lagrange functional (Lagrangian) :

$$L(\mathbf{w}, b, \alpha) = \frac{1}{2}(\mathbf{w} \cdot \mathbf{w}) - \sum_{i=1}^{L} \alpha_i \{[(\mathbf{x}_i \cdot \mathbf{w}) - b] y_i - 1\} \qquad (4)$$

Hence, the Lagrangian problem reduces to a Dual problem

$$\max_{\alpha} \ \min_{w,b} \ L(\mathbf{w}, b; \alpha) \qquad (5)$$

One obtains the Quadratic Programming (QP) problem as the dual problem in the Lagrange multiplies α_k (Vapnik, 1998; Li and Castagna, 2004). The QP problem has a number of properties unique solution and sparseness.

Case study

The Large-Save Field produces oil and gas from many horizons in many wells. The target horizon studied here produces from depths between 1600m to 1900m. In the project region there are 20 wells that have production information for the target horizon. Some wells produce large quantities of oil with low water cut, some produce oil with high water cut, some produce mostly water with some oil, some produce only water, and some do not flow at all. Of the total of 20 wells, 10 are commercial oil, 6 are non-commercial oil wells, and 4 produce no oil.

The aim of this study is to identify new positions for producing wells via supervised pattern recognition using SVM.

By choosing, we use 4 seismic attributes:
1. average energy;
2. instantaneous frequency;
3. mean amplitude;
4. mean impedance

From any single attribute map, it is not possible to identify the commercial oil wells.

We divide the known wells into two groups: one group for training and the other for validation. We selected 5 good commercial oil wells, 1 noncommercial oil well and 2 dry holes for training. The remaining 10 wells were used for validation. The result of the SVM classification is shown in Table 1. The test wells are 13 that 8 commercial oil, 3 non-commercial oil and 2 dry wells. The result is listed in table 2.

All but 2 commercial oil wells were correctly identified. In retrospect, it was determined that these two incorrectly classified wells were also gas wells, which were not present in the training dataset. Thus, it is important that the training dataset sample all the possible outcomes, or errors of this kind are to be expected. Even so, the success rate of correctly classifying the validation wells was 83%, while the success rate for identifying commercial oil wells was average 85%.

Table 1.

	Commercial oil	**Non-commercial oil**	**Dry**	**Total**
Training	5	1	2	8
Validation	6	2	2	10
Correct	5	2	2	9
Incorrect	1	0	0	1
Success %	83.3%	100%	100%	88%

Table 2.

	Commer-cial oil	**Non-commercial oil**	**Dry**	**Total**
Test	8	3	2	13
Correct	7	2	2	11
Incorrect	1	1	0	2
Success %	87.5%	66.7%	100%	84.6%

Conclusions

We present a new pattern recognition technique (SVM classifier) to classify 3D seismic volumes to predict oil producing reservoirs. This supervised learning approach based on a local basis function and the support vector principle has excellent generalization ability and can be used to avoid overtraining.

For the Large Save Field area 3D seismic volume and wells, we used 6 seismic attributes and selected well information as training data to build the SVM structure, and examined the performance of the machine with 10 remaining wells in area as test data. The results are that the ratio of correct classification as oil producing, non-commercial oil, and dry hole exceeded 85% for this application in this area.

References

Li, J., and J. Castagna (2004), Support Vector Machine (SVM) pattern recognition to AVO classification, *Geophys. Res. Lett*., **31**, L02609, doi:10.1029/2003 GL018299.
Kuzman, H., 2003, A support vector machine for AVO interpretation, 2003 SEG Abstracts, AVO 1., 181-184.
Vapnik,V., 1998, Statistics learning theory, John Wiley & Sons Inc.

Acknowledgments

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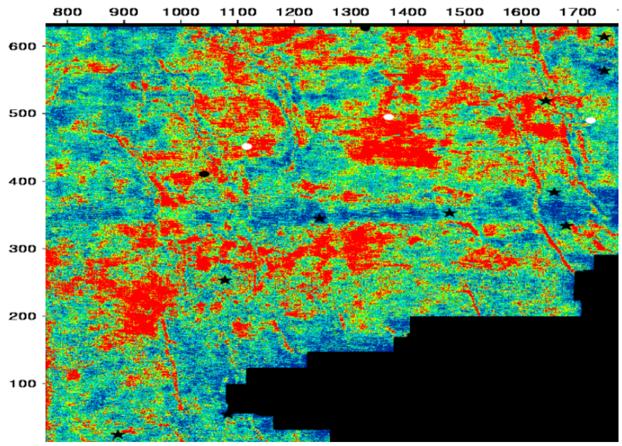
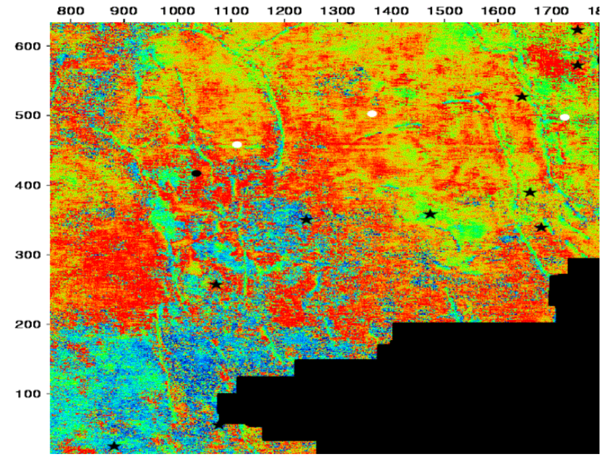
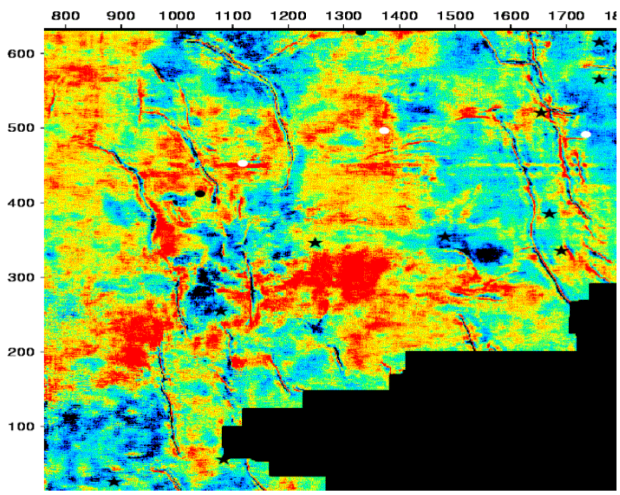
The following figures are seismic attributes maps (part):



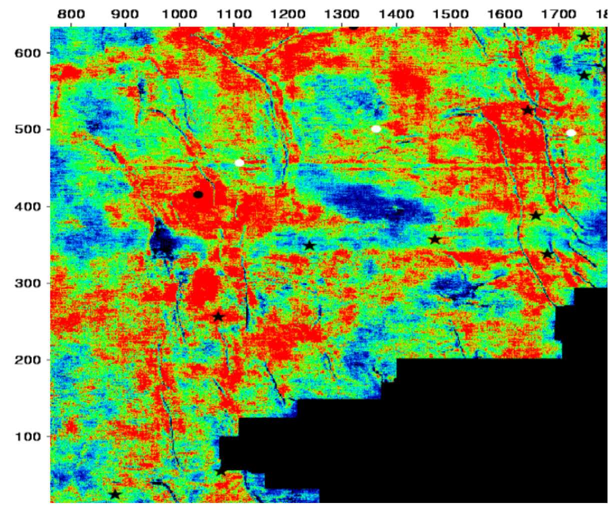
Average Energy



Instantaneous Frequency



Mean Amplitude



Mean Impedance

Prediction