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Geological reservoir property classification using artificial neural networks with optimal selection of seismic attributes

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Summary

An improved approach to classify seismic facies within a hydrocarbon reservoir using seismic data and artificial neural networks (ANN) is presented. The principal difficulty of this classification task consists in selecting the set of seismic attributes and the architecture of the ANN yielding the best classification ability. Conventionally, this attribute selection is based on data scaling and principal component analysis of the data and by iterative cross-validation using blind wells. Here, we propose a seismic attribute selection procedure based on direct orthonormalization of attributes and selecting attributes with the highest resolving ability with respect to the target classes. In addition, when visualizing and interpreting classification results, it is important to utilize the statistical confidence levels of class identification. These procedures are illustrated using 3-D stacked seismic and well-log datasets from an oil field in Iran. The results are compared to those from conventional ANN and probabilistic neural network (PNN) reservoir classification methods.

Introduction

Supervised machine learning is broadly used to classify reservoir rock into certain known classes using 3-D seismic and well-log data. The simplest and most popular algorithms for classification is the standard artificial neural network (ANN) and the probabilistic neural network (PNN). The success and quality of classification principally depends on the selection of target geological classes (seismic facies) and seismic attributes which allow separation of these classes.

In this study, we utilize data from Mansuri field in Iran and investigate classification in terms of four electrofacies EF1-EF4 interpreted from an ANN-based analysis of twelve well logs (Zahmatkesh et al., 2021). Electrofacies are identified by their distinctive physical and chemical characteristics related to a certain rock type, and also by fluid content within the volume assessed by the well-log analysis. Among these electrofacies, the first two classes are related to sandstone rocks (EF1 and EF2), and classes EF3 and EF4 are related to limestone rocks. Classes EF1 and EF3 contain rocks with the best reservoir quality, EF2 has a medium reservoir quality, and class EF4 with low porosity and high percentages of shale is considered as non-reservoir.

In the following sections, the approach to attribute selection and results of its application to ANN-based classification are described. The results are compared to classifications by conventional ANN and PNN algorithms and visualized taking into account the statistical confidence of classifications at every point within the reservoir.

Method

To utilize the maximum information from the seismic attributes, we start from the acoustic impedance (AI) and porosity extracted from stacked reflection seismic data and 23 additional attributes available from OpendTect software. However, multiple seismic attributes may also be noisy and insensitive to the target classification, and therefore the input set of attributes needs to be reduced and preconditioned for use in the ANN classification. Different selection and preconditioning procedures were used in the porosity estimation and in the preconditioning of the seismic attributes for final classification. These approaches are described below.

Acoustic impedance was acquired using model-based inversion with geological constraints which determine how far the final model is allowed to deviate from the initial model and how closely it should match the seismic data.

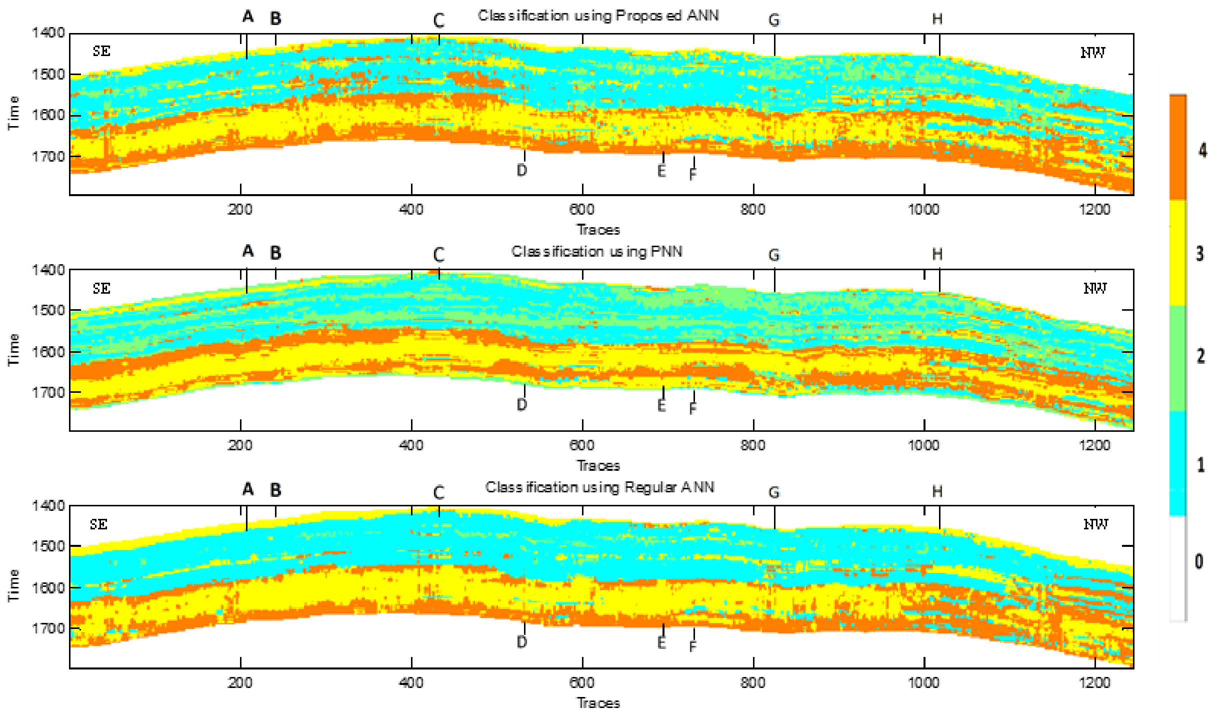
For porosity estimation, the, selection of attributes was done by a process called stepwise regression. The purpose of this procedure is to select a set of input attributes in this process, one or several wells are removed from the dataset and used for validation, i.e., checking how the algorithm is capable of predicting known but 'blind' data. In an iterative process, the prediction (cross-validation) error is minimized to find the best attribute, then the best pair of attributes, then the best triplet, and so on. Twelve wells and nine seismic attributes were used to estimate the porosity using machine learning techniques.

Finally, the machine learning techniques could apply nonlinear relations between multiple inputs and outputs and classify the entire reservoir into four known classes using a novel approach in selection of optimized set of attributes. The idea of this approach is in creating Nf binary classifications of the data from the known four classes using logistic regression and calculate probabilities pk for each of the binary classifications. Then, to reduce the dimensionality of the feature space and possible overfitting while having good representation of all four classes, we dropped the attributes with accuracy below 80%. The resulting dataset then contains 16 attributes. After orthogonalization and preconditioning, we further used the singular value decomposition to obtain the eigenvalues (variances) and eigenvectors (principal components), which represent the final new set of attributes. Lastly, we tested the performance of the algorithm using the 7 highest eigenvalues, and we reach a significant improvement in validation score compared to the conventional approach. Using these optimal attributes and a selected ANN structure, we investigate selection of the regularization parameters for its training step and then we used blind wells to validate the optimized parameters.

Results

Based on the known labels, we expect to see a near-continuous layer of class EF3 at the top of the classification cross-section (yellow in these figures), and also a continuous layer of class EF4 (brown) at the bottom of the cross-section. The ANN with optimized attribute selection ("proposed ANN", called P-ANN below) and the conventional ANN approaches successfully classify these zones with high accuracy, but the PNN results show neither continuous layer of class EF3 at the top nor continuous class 4 at the bottom of the section. At the same time, layering of seismic facies EF1 and EF2 within the upper half of the reservoir appears to be more pronounced and contiguous in the PNN classification.

The estimated confidence levels can also be used to create enhanced and easier to interpret images of the data. For example, to emphasize the subsurface areas with reliable classification, we create a filter (mask) for the image displaying the data only in areas with confidence $C \geq 70\%$ when using the ANN-based methods, or $C \geq 50\%$ when using the PNN. The filtered classifications for P-ANN and ANN are not showing class EF2, which means that all of its identification lies below the 70% confidence. For PNN, the 50% confidence threshold allows seeing all four classes nicely, except at the bottom of the section. Also, a significant observation with PNN is that class EF4 at the bottom of the plot is intermittent due to lower confidence.



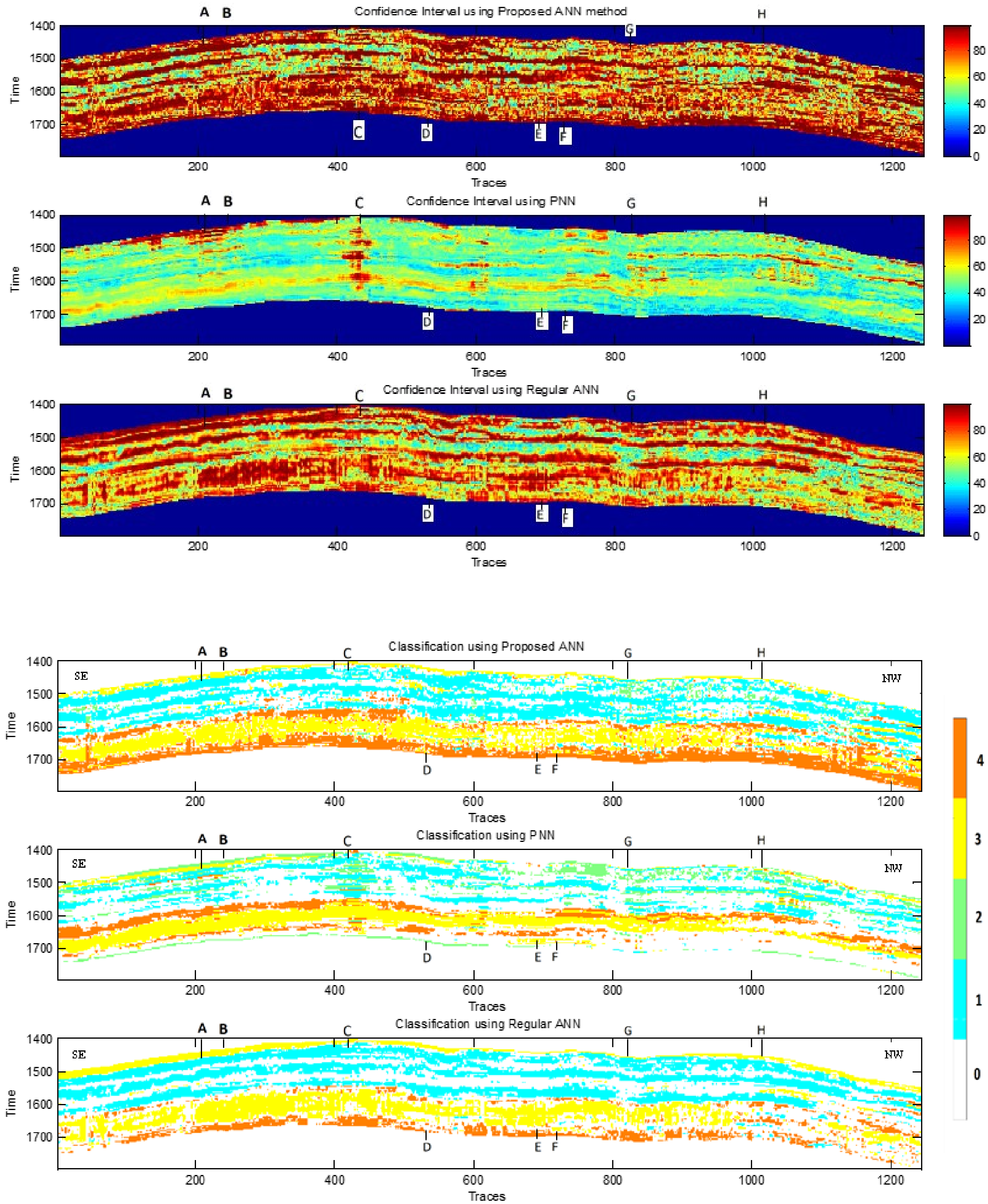


Fig 1: Classification cross-section (top), Confidence Interval (middle) and filtered seismic facies classification using probability of the predicted class (bottom).

Conclusions

Probabilities of the classes and statistical confidence estimates were obtained from three classification algorithms. Plotting of these quantities as seismic sections or volumes is useful for reservoir characterization and interpretation. By plotting zones with confidence levels above 0.7 (for P-ANN) or 0.5 (for PNN), I obtained images of reliable classifications of the reservoir since classes with low confidence level were removed.

Acknowledgements

Data were provided by NIOC. The EF1-EF4 classification from well logs is from (Zahmatkesh et al., 2021). Seismic attributes were derived by OpendTect software. Hampson-Russell STRATA software was used for acoustic impedance inversion, porosity estimation, and PNN classification. Data analysis was performed using Matlab and Python software.

References

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