**An Information Theoretic Framework to Predict Lithological Properties from Multiple Seismic Attributes**

*Soumi Chaki, Deepan Data*, Aurobinda Routray, William K. Mohanty (IIT Kharagpur),*
*Sanjai Kumar Singh, Rajeev Tandon, CS Bahuguna (GEOPIC, ONGC, Dehradun)*
*(*dattadeepan@gmail.com)*

**Keywords**

Artificial neural network, Fourier transform, preprocessing, regularization, reservoir characterization (RC), sand fraction, 3-D median filtering, wavelets.

**Summary**

This paper represents multiple seismic attributes such as seismic amplitude, frequency and impedance using information filtering and machine learning to improve the prediction of sand fractions. The conjugate-gradient learning algorithm with artificial neural network (ANN) has been used to model the sand fraction. The data available from well logs have very high-resolution than the low-resolution seismic attributes. Therefore, Fourier transform (FT) as a regularization scheme has been proposed to shape the high-resolution sand fraction data for machine learning. Then input data sets have been segregated into validation, testing and training sets. The results used to check different network structures and function performances. Once the test passes with an acceptable performance, the validation phase follows. Then prediction model is tested against unseen data. The network gives satisfactory performance in the stage validation is used to predict lithological properties from seismic volume. Finally a 3-D spatial filtering is implemented using post-processing scheme for smoothing the sand fraction in the volume. This gives the predictions of lithological properties for reservoir characterization.

**Introduction**

Hydrocarbons migrate from source rock through porous medium to reach reservoir rock for temporary preservation [1]. Finally, the mobile hydrocarbons get seized in the cap rocks. As such, the identification of hydrocarbon enriched formations by characterization of each layer in the borehole is of enormous importance to the explorers. Recognition of potential hydrocarbon-enriched zones in a prospective oil exploration field can be carried out using well logs which can categorize layers into different sections such as dry, water-containing, and hydrocarbon-bearing layers. The lithological properties in the neighborhood of a borehole can be estimated from well logs, whereas their distributions become difficult to predict away from the wells. In such cases, avail- able seismic attributes can be used as a guidance to predict lithological information at all traces of the area of interest [2]. Well logs and seismic attributes are integrated at available well locations to design a reservoir model with the least uncertainty. However, mapping between well logs and seismic attributes is governed by nonlinear relationship and characterized by mismatch in information content. Such nonlinear problems can be approached using state-of-art computer-based methods like hybrid systems [3], [4], multiple regression, neural networks [5], neuro-fuzzy systems [6]-[9], Support Vector Data Description (SVDD) [10]-[11], etc.

This paper proposes a novel preprocessing scheme and demonstrates the use of the said scheme in an appropriately designed framework, consisting of three stages— preprocessing, modeling, and post processing, to estimate sand fraction (SF) from multiple seismic attributes. Here, the target variable SF represents per unit sand volume within the rock.

**Methodology**

The workflow starts with preprocessing stage, which uses three alternative approaches for target variable regularization based on FT. Next, a functional relationship between the regularized target SF and the seismic attributes is calibrated using ANN. In this study, a simple network structure consisting of a single hidden layer is selected over relatively complex networks. The network parameters and training algorithm are decided empirically. The results obtained are evaluated in terms of four performance indicators—correlation-coefficient (CC), root mean square error (RMSE), absolute error

In order to establish the efficacy of the proposed regularization method, the task of model building and validation stage is carried out using both the original and regularized SF as target variable. The training dataset is created by aggregating 70% sample patterns from each of the wells. The training patterns are scrambled to remove any possible trend along the depths. The remaining 30% samples from each of the four wells are combined and then divided into two parts to create the testing and the validation datasets. First, the network is trained using training patterns with initial parameter values. Then, the network structure and activation functions are tuned using testing patterns. The testing phase is important for evaluating the generalization capability of the trained network [8].

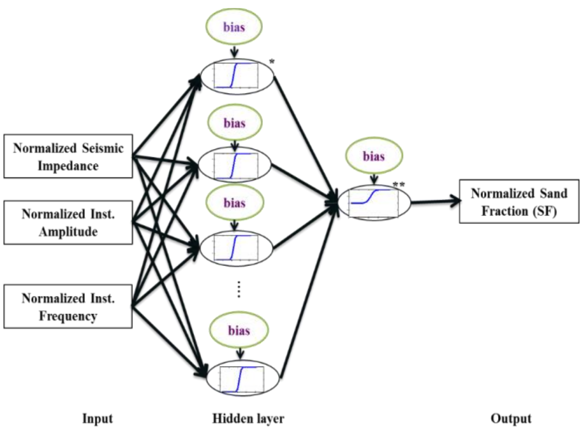


Figure 5. Network Structure; Transfer Function (Hidden Layer) : Hyperbolic tangent sigmoid, Activation Function : Log-sigmoid

*Postprocessing*

It can be observed from Fig. 6 that the variation in the seismic attributes over the study area is smooth. However, the SF across the study area as shown in Fig. 7 changes abruptly. The transition of the SF values should be smoother and more or less agree to the patterns of seismic data, thereby raises the need for the post-processing stage to obtain a smoother SF variation across the volume. To incorporate this rationale, the predicted values are filtered through a 3-D median filter. In case of order statistics filtering, the window size is selected to define the neighborhood around the centered pixel. Selection of window value is crucial for the degree of smoothing.

The predicted SF in the volume is used as input to the post-processing operation. Every element in the volume is considered as a pixel and is smoothened using 3-D median filter with respect to its neighborhood within a 3 × 3 × 3 window size. The missing values along the boundaries are ignored. In order to carry out median filtering, the values of the pixel and its neighbors within the selected window are first sorted. Then, the centered pixel value is replaced by the median value determined from the sorted pixel values.

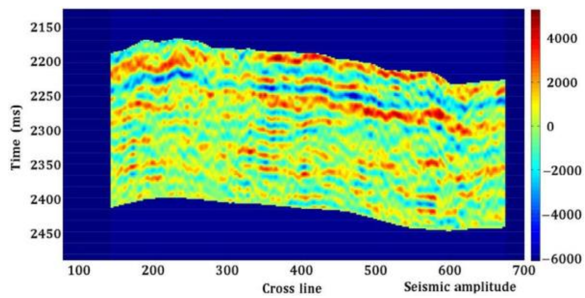


Figure 6. Variation in the seismic amplitude at inline 136.

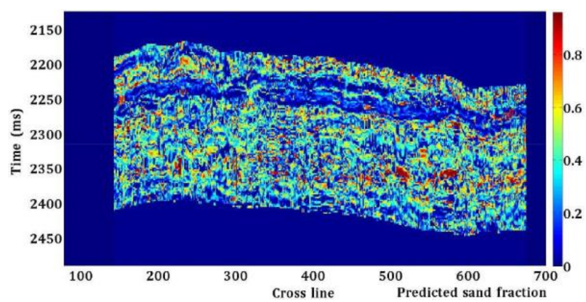


Figure 7. Variation in the predicted SF at inline 136.

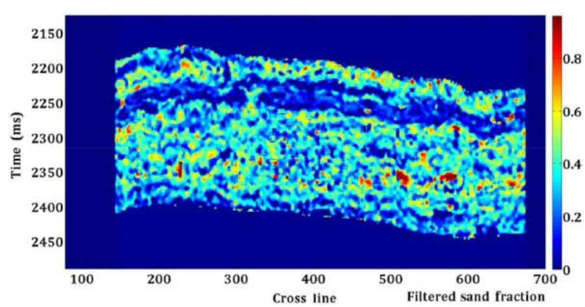


Figure 8. Result of 3-D median filtering with a $3 \times 3 \times 3$ window on the predicted SF variation at inline 136.

Fig. 8 represents the result of median filtering along inline 136. The effect of localizing different levels of

SF values can be observed by comparing Figs. 7 and 8.

## Conclusion

The selection of initial parameters is crucial for achieving acceptable performance of ANN. In the present work, the ANN structure and activation functions in hidden and output layers have been empirically adjusted. Also, the initial values of weight and bias matrices have been chosen randomly. As a possible future extension, the domain of metaheuristic algorithms can be explored to automate such selections to further strengthen the framework. Additionally, while in the post-processing stage, the use of spatial filtering has provided a significant improvement in the SF variation over the study area; adaptive post-processing method can be investigated in future.

## Acknowledgement

This work has been undertaken by Indian Institute of Technology, Kharagpur in collaboration with Geo data Processing & Interpretation Centre (GEOPIC), ONGC, Dehradun.

## References

[1] G. Álvarez, B. Sansó, R. J. Michelena, and J. R. Jiménez, "Lithologic characterization of a reservoir using continuous-wavelet transforms," IEEE Trans. Geosci. Remote Sens., vol. 41, no. 1, pp. 59–65, Jan. 2003.

[2] M. Bosch, T. Mukerji, and E. F. Gonzalez, "Seismic inversion for reser- voir properties combining statistical rock physics and geostatistics: A review," Geophysics, vol. 75, no. 5, pp. 75A165–75A176, Sep. 2010.

[3] M. Ali Ahmadi, S. Zendehboudi, A. Lohi, A. Elkamel, and I. Chatzis, "Reservoir permeability prediction by neural networks combined with hybrid genetic algorithm and particle swarm optimization," Geophys. Prospect., vol. 61, no. 3, pp. 582–598, May 2013.

[4] S. Yu, X. Guo, K. Zhu, and J. Du, "A neuro-fuzzy GA-BP method of seismic reservoir fuzzy rules extraction," Expert Syst. with Appl., vol. 37, no. 3, pp. 2037–2042, Mar. 2010.

[5] D. P. Hampson, J. S. Schuelke, and J. A. Quirein, "Use of multiattribute transforms to predict log properties from seismic data," Geophysics, vol. 66, no. 1, pp. 220–236, Jan. 2001.

[6] P. M. Wong, A. G. Bruce, and T. T. D. Gedeon, "Confidence bounds of petrophysical predictions from conventional neural networks," IEEE Trans. Geosci. Remote Sens., vol. 40, no. 6, pp. 1440–1444, 2002.

[7] A. K. Verma, S. Chaki, A. Routray, W. K. Mohanty, M. Jenamani, "Quantification of sand fraction from seismic attributes using Neuro-Fuzzy approach," J. Appl. Geophysics, vol. 111, pp. 141-155, Dec. 2014.

[8] I. Kaastra and M. Boyd, "Designing a neural network for forecasting financial and economic time series," Neurocomputing, vol. 10, pp. 215– 236, 1996.

[9] S. Chaki, A. K. Verma, A. Routray, M. Jenamani, W. K. Mohanty, P. K. Chaudhuri, and S. K. Das, "Prediction of porosity and sand fraction from well log data using ANN and ANFIS : a comparative study," in 10th Biennial Int. Conf. Expo. SPG, Kochi, India, 2013.

[10] S. Chaki, A. K. Verma, A. Routray, W. K. Mohanty, and M. Jenamani, "A one-class classification framework using SVDD : application to an imbalanced geological dataset," in Proc. IEEE Students' Technology Symp. (TechSym), Kharagpur, India, 2014, pp. 76–81.

[11] S. Chaki, A. K. Verma, A. Routray, W. K. Mohanty, and M. Jenamani, "A novel framework based on SVDD to classify water saturation from seismic attributes," in Fourth International Conference of Emerging Applications of Information Technology (EAIT), Kolkata, India, 2014, pp. 64–69.

[12] N. Sharma and M. M. Ali, "A neural network approach to improve the vertical resolution of atmospheric temperature profiles from geostationary satellites," IEEE Geosci. Remote Sens. Lett., vol. 10, no. 1, pp. 34–37, Jan. 2013.

[13] S. Chaki, A. Routray, and W. K. Mohanty, "A novel pre-processing scheme to improve the prediction of sand fraction from seismic attributes using neural networks," IEEE J. Sel. Topics Appl. Earth Observations and Remote Sens., vol. 8, no. 4, pp. 1808-1820, 2015.

[14] S. Chaki, A. K. Verma, A. Routray, W. K. Mohanty, and M. Jenamani, "Well tops guided prediction of reservoir properties using modular neural network concept: A case study from western onshore, India," J. Pet. Sci. Eng., vol. 123, pp. 155-163, Nov. 2014.

[15] A. Douillard, D. Schlumberger, and O. Balz, "Upscaling well logs to seismic scale–Comparison of a wavelet-transform based method with a geostatistical technique," in Petrophysics Meets Geophysics, Nov. 2000, pp. 1–9.

[16] T. M. Cover and J. A. Thomas, Elements of Information Theory. Hoboken, NJ, USA: John Wiley & Sons, Inc., 1991.

[17] T. Mukerji, P. Avseth, G. Mavko, I. Takahashi, and E. F. González, "Statistical rock physics: combining rock physics, information theory, and geostatistics to reduce uncertainty in seismic reservoir characterization," Lead. Edge, vol. 20, no. 3, pp. 313–319, Mar. 2001.