International Journal of Computer Science and Information Technology
ISSN: 3005-9682 (Print), ISSN: 3005-7140 (Online) | Volume 3, Number 2, Year 2024
DOI: https://doi.org/10.62051/ijcsit.v3n2.46
Journal homepage: https://wepub.org/index.php/IJCSIT/index

Comprehensive Review on Seismic Facies Identification

Rui Liang

Chengdu University of Technology, Chengdu, China
1297119404@qq.com

ABSTRACT

Seismic facies identification is crucial for interpreting subsurface geological features and predicting reservoir properties. This review discusses the methodologies, advancements, and applications in seismic facies identification, including traditional approaches, machine learning techniques, and case studies. The aim is to provide a thorough understanding of the current state and future directions in this field.

KEYWORDS

Seismic Facies Identification; Seismic Stratigraphy; Seismic Attributes; Machine Learning; Deep Learning; Reservoir Characterization; Hydrocarbon Exploration

1. TRADITIONAL APPROACHES

1.1. Seismic Stratigraphy

Seismic stratigraphy involves analyzing seismic data to identify stratigraphic units and interpret depositional environments. The principles of sequence stratigraphy and seismic reflection terminations (such as onlap, downlap, toplap, and erosional truncation) are used to delineate stratigraphic boundaries and interpret facies. The main objective of seismic stratigraphy is to identify different depositional sequences over geological time, providing insights into the formation and evolution of strata. This method is particularly important in hydrocarbon exploration for identifying potential reservoir and cap rocks.

$$S_{reflection} = \sum_{i=1}^{n} R_i \,.\, e^{2\pi i f t_i}$$

Where:

$S_{\mathrm{reflection}}$ is the seismic reflection signal.

R_i is the reflection coefficient.

f is the frequency.

ti is the travel time.

1.2. Seismic Attributes

Seismic attributes are derived from seismic data and enhance the visibility of geological features. Common attributes include amplitude, phase, frequency, and coherence, which help highlight discontinuities, faults, and stratigraphic features not easily visible in raw seismic data. Amplitude attributes reveal interfaces between different rock and fluid types, phase attributes indicate the timing and relative position of seismic events, frequency attributes help identify spectral characteristics of different lithologies, and coherence attributes are used to detect discontinuities such as faults and fractures.

Table 1. Seismic Signal Attributes

Attribute	Description
Amplitude	Reflects the strength of the seismic signal
Phase	Indicates the timing of seismic events
Frequency	Shows the distribution of seismic signal frequencies
Coherence	Measures the similarity of seismic waveforms, useful for detecting faults

1.3. Well Log Integration

Integrating well log data with seismic data improves the accuracy of facies identification. Well logs provide direct measurements of rock properties, which can be correlated with seismic attributes to better understand subsurface geology. Well log data include parameters such as resistivity, sonic velocity, and density, which can be used to calibrate seismic data, thus enhancing the precision of seismic facies analysis. By correlating well log data with seismic attributes, it is possible to identify regions with similar characteristics and infer subsurface geological structures.

$$V_p = \sqrt{\frac{K+\frac{4}{3}\mu}{\rho}}$$

Where:

Vp is the P-wave velocity.

K is the bulk modulus.

μ is the shear modulus.

ρ is the density.

2. ADVANCES IN MACHINE LEARNING

2.1. Supervised Learning

Supervised learning techniques, such as neural networks and support vector machines, classify seismic facies by learning the relationship between seismic attributes and facies types from labeled training data. These algorithms rely on a large amount of known facies samples to train the model to predict facies types in unknown data. For example, neural networks can handle complex nonlinear relationships, while support vector machines are suitable for classifying high-dimensional data. The accuracy of these methods largely depends on the quality and quantity of the training data.

$$y = f(X) = W \cdot X + b$$

Where:

y is the predicted output.

X is the input feature vector.

W is the weight matrix.

b is the bias vector.

2.2. Unsupervised Learning

Unsupervised learning methods, such as k-means clustering and self-organizing maps, classify seismic facies by identifying natural groupings in the data without labeled samples, revealing new facies types or refining existing classifications. K-means clustering divides the data by minimizing the distance between data points and their respective cluster centers, while self-organizing maps, a type of neural network, reduce the data's dimensionality and visualize patterns to help geologists understand the data's structure. These methods are particularly useful when there are many unknown features in the seismic data or when labeled data is scarce.

2.3. Deep Learning

Deep learning, particularly convolutional neural networks (CNNs), has shown great promise in seismic facies identification. CNNs automatically learn hierarchical features from seismic data, improving classification accuracy and reducing the need for manual feature extraction. The multi-layer structure of CNNs can capture complex patterns in seismic data, from basic features in lower layers to abstract features in higher layers, making them highly effective for processing large-scale and complex seismic datasets. Additionally, deep learning can be combined with other machine learning methods to further enhance seismic facies identification.

3. APPLICATIONS

3.1. Reservoir Characterization

Seismic facies analysis is essential for reservoir characterization, helping to identify reservoir boundaries, heterogeneity, and connectivity, which are critical for reservoir management and production optimization. By analyzing seismic facies, key parameters such as reservoir thickness, porosity, and permeability can be determined, guiding drilling and completion operations. Furthermore, seismic facies analysis can identify high-productivity and low-productivity zones within the reservoir, optimizing well placement and enhancing hydrocarbon recovery.

3.2. Hydrocarbon Exploration

In exploration, seismic facies analysis assists in predicting potential hydrocarbon reservoirs' locations by interpreting depositional environments and identifying regions with favorable conditions for hydrocarbon accumulation. Seismic facies analysis can identify depositional, structural, and lithological facies, predicting the distribution and enrichment patterns of hydrocarbons. For example, by identifying fluvial channels, deltas, reefs, and other depositional facies, the reservoir environment and migration pathways of hydrocarbons can be inferred, guiding the selection of exploration targets and drilling locations.

3.3. Environmental and Engineering Geophysics

Seismic facies identification is used in environmental and engineering geophysics to understand subsurface conditions for infrastructure development and environmental assessments. Through seismic facies analysis, subsurface conditions such as aquifers, contaminant pathways, and geological hazards can be identified, providing scientific support for environmental protection and engineering construction. For example, in large engineering projects, seismic facies analysis can evaluate the stability and suitability of the foundation, avoiding engineering accidents due to poor geological conditions.

4. CASE STUDIES

4.1. North Sea Basin

In the North Sea Basin, seismic facies analysis has been pivotal in identifying and characterizing multiple reservoir units. Integrating seismic attributes and well log data, geoscientists have delineated complex stratigraphic features and improved hydrocarbon predictions. In this region, seismic facies analysis has successfully identified multiple hydrocarbon reservoirs and potential exploration targets, increasing exploration success rates and economic benefits.

4.2. Gulf of Mexico

The Gulf of Mexico presents challenges due to its complex geology. Seismic facies analysis enhanced by machine learning techniques has led to a better understanding of deepwater reservoirs and improved exploration success rates. Utilizing deep learning methods, researchers have been able to more accurately identify seismic facies in deepwater areas, improving the prediction accuracy and reliability of reservoirs, thereby reducing exploration risks and costs.

5. CHALLENGES AND FUTURE DIRECTIONS

5.1. Data Quality and Availability

The quality and availability of seismic data are critical for accurate facies identification. Efforts to improve data acquisition techniques and access to high-quality data are ongoing. For example, advancements in 3D seismic survey technology have significantly increased data resolution and accuracy, providing more detailed and reliable data for seismic facies analysis. However, the costs and technical requirements for data processing and storage have also increased, necessitating further technological innovation and optimization.

5.2. Algorithm Development

Advancements in algorithm development, particularly in machine learning, will continue to enhance seismic facies analysis. Future research should focus on developing more robust and interpretable models. Current machine learning models perform well with complex seismic data but face challenges in interpretability and robustness. For example, understanding the decision-making process of deep learning models and improving model generalization in the absence of labeled data are ongoing research issues.

5.3. Integration with Other Data Sources

Integrating seismic data with other geophysical and geological data sources will provide a more comprehensive understanding of subsurface conditions. Multidisciplinary approaches will be key to advancing the field. For instance, combining seismic data with gravity, magnetic, and electrical methods can improve the interpretation accuracy and reliability of subsurface structures. Additionally, integrating seismic data with geological, petrophysical, and geochemical data can create more detailed and comprehensive subsurface models, guiding hydrocarbon exploration and development.

Table 2. Geophysics Data Sources and Their Integration Benefits

Data Source	Integration Benefit
Gravity Data	Enhanced subsurface density mapping
Magnetic Data	Improved understanding of magnetic properties
Electrical Methods	Better identification of resistivity anomalies

6. CONCLUSION

Seismic facies identification is a dynamic field with significant advancements in traditional methods and machine learning techniques. Continued research and technological developments will further enhance our ability to interpret seismic data and predict subsurface geological features. As data acquisition and processing technologies advance, and machine learning and deep learning algorithms are continuously optimized, seismic facies identification will become more precise and efficient, providing stronger support for hydrocarbon exploration and development.

REFERENCES

[1] Sheriff, R.E., & Geldart, L.P. (1995). Exploration Seismology. Cambridge University Press.

[2] Brown, A.R. (2011). Interpretation of Three-Dimensional Seismic Data. AAPG Memoir 42.

[3] Chopra, S., & Marfurt, K.J. (2007). Seismic Attributes for Prospect Identification and Reservoir Characterization. SEG.

[4] Wu, X., & Hale, D. (2016). Convolutional neural networks for fault interpretation in seismic images. Geophysics, 81(4), IM21-IM32.

[5] Zeng, H., & Backus, M. (2005). Interpretation of seismic inversion results using reservoir facies. Geophysics, 70(5), P47-P56.

[6] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436-444.

[7] Abreu, V., Sullivan, M., Pirmez, C., & Mohrig, D. (2003). Lateral accretion packages (LAPs): An important reservoir element in deep water sinuous channels. Marine and Petroleum Geology, 20(6-8), 631-648.

[8] Litenberg, J.H. (2005). Detection of fluid migration pathways in seismic data: implications for fault seal analysis. Basin Research, 17(1), 141-153.

[9] Gao, D. (2007). Application of three-dimensional seismic texture analysis with special reference to deep-marine facies interpretation: a case study from the Gulf of Mexico. AAPG Bulletin, 91(2), 166-183.

[10] Zhang, R., & Castagna, J.P. (2011). Seismic lithology classification using multivariate analysis. Geophysics, 76(2), C23-C34.