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Hierarchical SOMs: Bridging Local and Global Patterns in Multi-Attribute Seismic Data

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Summary

Seismic angle gathers and spectral seismic attributes offer complementary insights to improve understanding of complex subsurface characteristics. However, the labor-intensive process of subsurface characterization, data annotation, limited labeled data, and subsurface complexity make it difficult to leverage these insights via supervised learning approaches.

To overcome such challenges and benefit from the strength of spectral seismic attributes, this study introduces a novel hierarchical Self-Organizing Map (SOM) framework to integrate spectral seismic attributes like scalograms and spectrograms (joint time-frequency analyses) extracted from angle gathers.

In our current research, firstly, we trained individual SOMs, as an unsupervised pattern recognition algorithm on reflectivity images, angle-gathers, and the spectral seismic attributes extracted from angle-dependent data. Secondly, we deploy a hierarchical SOM network to combine and analyze all these datasets. Thirdly, we evaluate the hierarchical approach and standalone analyses of clustering quality and information content using the binary boundary maps and the performance metrics. Our findings indicated that, the scalogram-based hierarchical SOM, containing information of different angles, achieves the lowest Quantization Error and Davis-Bouldin Index, indicating optimal feature representation and well-separated clusters. The findings stress the potential of hierarchical networks and joint time-frequency analyses from angle gathers for robust seismic interpretation workflows.

Hierarchical SOMs: Bridging local and global patterns in multi-attribute seismic data analysis

Introduction

Characterization of subsurface structures is a crucial step in many geo-related projects such as geothermal, CCS, and mining projects (Brown, 2022). Advanced machine learning methods have the potential to accelerate this step (Lin et al., 2024). Consequently, many researchers have adopted various deep learning approaches, primarily supervised learning (Zheng et al., 2019). The main challenge with this learning strategy is its dependence on extensive training, requiring large volumes of labeled data. Data annotation, as an integral part of this process, poses significant difficulties, such as being time-consuming and requiring domain expertise to ensure accuracy. Labelling certain structures accurately can be subjective (Di and Abubakar, 2022). Thus, unsupervised machine learning algorithms may help to overcome these challenges (Mansoor, 2021). A second aspect is that seismic attributes are often derived from reflectivity images, neglecting varying angles of incidence (Chopra and Marfurt, 2005; Fomel, 2007). Extracting them across multiple angles can provide compre-hensive information (Veeken and Rauch-Davies, 2006). In this study, we investigate two key questions: 1. How do different types of seismic spectral attributes (scalograms vs. spectrograms), together with angle-dependency, perform in SOMs and hierarchical SOM networks? 2. Do hierarchical SOM networks enhance clustering and pattern recognition compared to standalone SOMs?

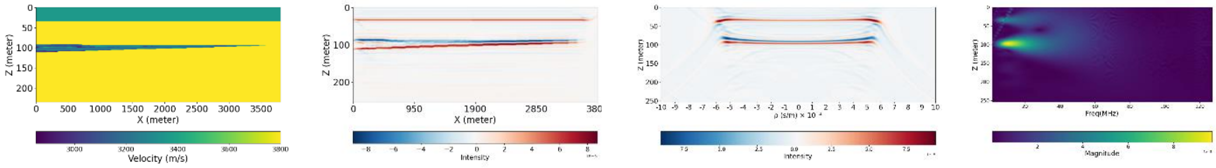
Theory

Joint time-frequency analysis methods as a seismic attribute provide additional insights into seismic signals. Among seismic attributes, spectrograms, are based on short-time Fourier transforms and offer fixed-window frequency representations (Allen and Rabiner, 1977), while scalograms deploy wavelet transforms for adaptive time-frequency analysis (Mallat, 1999). These two methods have been widely used in seismic spectral decomposition and attribute extraction (Castagna et al., 2003). It is worth mentioning that time–frequency analysis of seismic signals are often applied on reflectivity images to reveal the local properties. Therefore, in traditional seismic imaging, the information from various angles of incidence are usually being neglected (Davydenko and Verschuur, 2017). Incorporating angle of incidence information into reflectivity analysis, can enhance resolution and interpretability in seismic imaging (Davydenko and Verschuur, 2017; Sava and Fomel, 2003).

A self-organizing map (SOM), as described by Kohonen (1982), is a powerful nonlinear data visualization and clustering technique. This unsupervised neural network approach lowers the dimensionality of complex datasets. SOMs address the challenge of interpreting high-dimensional seismic attributes by projecting them onto a 2D map, where similar data points are grouped, generating the so-called Unified Distance Matrix and Binary boundary maps (BBM) (Yin, 2008). This ability can be deployed to identify and cluster patterns in seismic data analysis, which is particularly valuable for recognizing subsurface features that are difficult to detect. As a result, SOM analysis simplifies data interpretation and uncovers natural organizational structures within seismic attributes, such as clusters tied to lithological interfaces or amplitude anomalies. Therefore, SOMs enable robust pattern recognition and clustering. This ability assists in forming the foundation for advanced methodologies such as hierarchical SOM networks used in this study (Roden et al., 2015). This clustering technique iteratively combines pairs of individual observations based on the squared Euclidean distances between observations. The algorithm then combines these subclusters containing two observations into larger clusters using the same distance metric to assess similarity. For hierarchical networks, we use Ward's method to create the clusters (Gong and Richman, 1995), which assures that at each formation of a larger cluster, there is a minimum increase in total within-cluster variance after merging.

Methodology

For this analysis, to generate the geological simulations, a recently-developed Python package called pyBarsim, is used . The simulations are composed by a grid of 2x2 m cells where the mass-density and p-wave velocity is calculated based on the particular grain size distribution of each cell (Storms, 2003). The models were designed to represent geological trends, such as coarsening and thinning upward sequences in shallow marine depositional environments, with gradual property changes in every direction (Cuesta Cano et al., 2025). To simulate seismic responses, an acoustic 2D finite-difference method was applied to these models, incorporating a simple overburden with a few geological layers. A target-oriented full wavefield migration technique (Davydenko and Verschuur, 2017) generated both reflectivity images and angle gathers along the lateral axis. The angle gathers are divided into four groups: zero, near, mid, and far angles (Karimzadanzabi et al., 2024). Further, we compute the spectrogram and scalogram for each angle group (Castagna et al., 2003). **Figure 1** illustrates a sample of the geological model, its associated reflectivity, one angle gather at x=1900 m, and the corresponding scalogram for zero angle.



a) P-wave velocity model   b) Reflectivity   c) Angle gather   d) Scalogram

***Figure 1** The sample geological model, its corresponding reflectivity, the angle gather at x=1900 m, and the zero-angle scalogram.*

Additionally, we train individual self-organizing maps (SOMs) on each of these datasets separately (the first three rows in the **Table 1**). Next, the Best Matching Unit (BMU) features from all categories are concatenated horizontally to form a unified feature matrix. This matrix is then used to train a second SOM, referred to as the hierarchical SOM (Unglert et al., 2016). During this step for each group hierarchical networks are trained (the last row in the **Table 1**). For ease of reference, all categories and their corresponding datasets are presented in **Table 1**. To enhance readability, the acronyms listed in this table will be used consistently throughout the remainder of this paper.

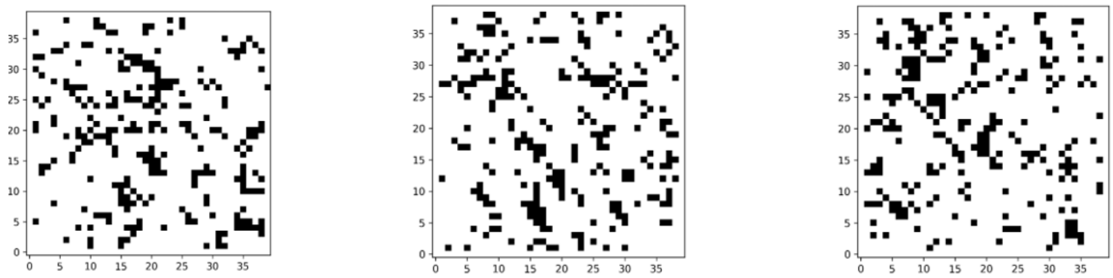
Table 1 Overview of Dataset Categories, Corresponding Names and Acronyms (the number inside bracket presents the dataset number)

Scalogram (Sc)	[1] Far Angle (Sc-F), [2] Mid Angle (Sc-M), [3] Near Angle (Sc-N)
Spectrogram (Sp)	[4] Far Angle (Sp-F), [5] Mid Angle (Sp-M), [6] Near Angle (Sp-N), [7] Zero Angle (Sp-Z)
Time-Domain (Td)	[8] Angle Gather (Td-A), [9] Reflectivity (Td-R)
Hierarchal (H)	[11] Scalogram (H-Sc), [12] Spectrogram (H-Sc), [13] Time-Domain (H-Td), [14]All (H-All)

To evaluate the performance, for each network, we calculate metrics: (1) Binary Boundary maps (BBMs) are used to visualize the boundaries between clusters or regions in the map and quantifies the presence or absence of boundaries between clusters. (2) Next, the key performance metrics: the quantization error (QE), the Silhouette Score (SS), and, lastly, the Davis-Bouldin Index (DBI) will be investigated. The QE is a key measure used to evaluate the performance of the SOM map in representing the input data. SS measures cluster cohesion and separation. An SS value close to 1 indicates a well-separated and cohesive cluster evaluated them at the point level. The SS is more sensitive to overlapping clusters. The third metric, DBI, is used to evaluate the clustering quality of different datasets and compares clusters at the cluster level, with lower values indicating better-defined and more separated clusters. The DBI is more sensitive to differences in cluster compactness (Yin, 2008; Liu et al., 2020).

Results and discussion

The results of individual SOMs and hierarchical SOMs were compared using two distinct strategies: First, the three best-performing hierarchical SOMs were analyzed in detail through matrix representations and corresponding simplified boundary maps. These visualizations provide insights into the spatial delineation of subsurface patterns and clusters. Second, to quantify the effectiveness of individual and hierarchical SOMs, we evaluated and compared the 3 key performance metrics across all datasets presented in ***Table 1***. The simplified BBMs for the three hierarchical networks are shown in ***Figure 2, Panels A to C***. In the binary representation, black areas represent boundaries between clusters with greater heterogeneity, while white patches indicate closely related data points, implying that these areas in the SOM correspond to similar features or categories. For the H-Td dataset, scattered pattern of white areas in binary boundary map suggested that clusters were smaller and less distinct, with a moderate level of cluster definition (***Figure 2 panel A***). While, the binary boundary map for dataset H-Sc and H-Sp reveals larger, more cohesive white areas with fewer distinct groupings or more homogeneous patterns across different angles. This is in close relation with the fact that scalograms and spectrograms are known to provide broader, less fragmented representations of time-frequency information, which is reflected in the sparse boundaries (***Figure 2 panel B and C***).



Panel a) H-Td Panel b) H-Sc Panel c) H-Sp

Figure 2 *The Binary Boundary map (BBM) representations.*

As shown in ***Figure 3***, among the other training data sets, the H-Td and H-Sc have the lowest QE. This suggests a better balance between the actual input data and how the SOM's neurons represent it. Whereas the H-All has the highest QE, likely due to the heterogeneity and complexity of the combined data. Same behaviours are perceived from the H-Sp, which indicates the heterogeneity of the spectrogram for different angles. In contrast to scalograms, spectrograms employ fixed window lengths for processing rather than adjusting to the structure of the signal. Thus, the H-Sc result in the lowest QE, show casing the homogeneous nature of the scalograms. This make the scalogram from different angles a good candidate for hierarchical networks, because they require a consistent representation of features across varying perspectives to ensure robust learning and accurate feature extraction.

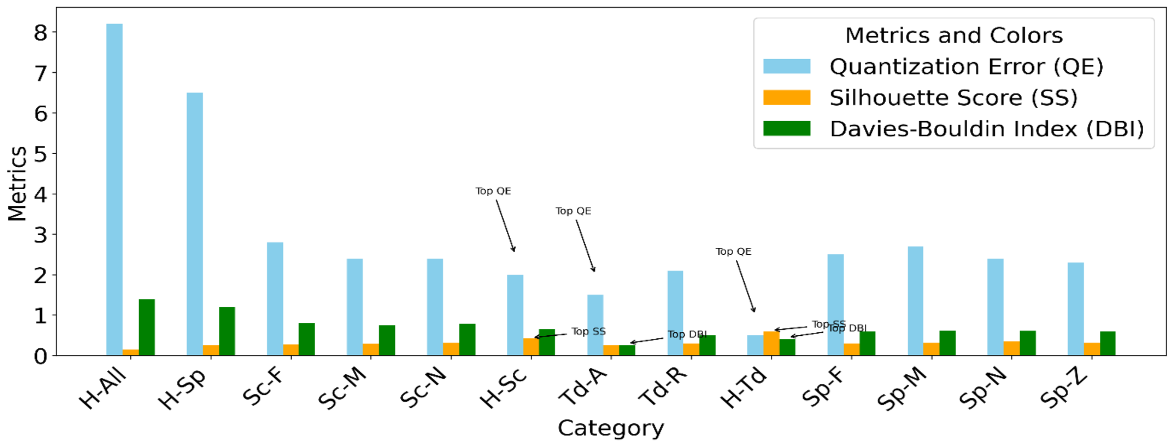


Figure 3 *Key performance metrics for all datasets.*

As shown in Figure 3, H-Sc and H-Td, exhibit the highest values among the datasets, indicating more robust clustering. Conversely, clusters with an SS value closer to 0, such as H-All, suggest overlapping or poorly defined clusters. All other training datasets display similar SS values, emphasizing the superiority of hierarchical networks in clustering strength, particularly when each individual training dataset used to create them represents a homogeneous pattern, as seen with H-Sc. It is worth noting that the closeness of SS values within Sp-F, Sp-M, Sp-N, and Sp-Z does not necessarily demonstrate a homogeneous pattern conducive to a well-separated hierarchical network. As shown in this ***Figure 3***, H-Sc and H-Td achieve the lowest DBI values, highlighting their superior clustering performance. This suggests that these datasets represent cohesive and well-separated clusters, making them the most robust among the evaluated categories (Liu et al., 2020).

Conclusions

This study introduces a hierarchical Self-Organizing Map (SOM) methodology for integrating multi-attribute seismic data, focusing on spectral attributes like scalograms and spectrograms from angle gathers. Our realistic geological simulations are characterised by gradual changes in properties. The results demonstrate that hierarchical SOM networks outperform individual SOMs by enhancing clustering quality and subsurface pattern recognition. Scalograms emerge as the most effective input, yielding homogeneous and well-separated clusters due to their adaptability to time-frequency variations, as evidenced by low QE, DBI and high SS values. In contrast, spectrograms and combined datasets (H-All) exhibit higher QE and DBI, reflecting greater heterogeneity and overlap in clusters. These findings are supported by binary boundary map analyses, which visually confirm the clustering patterns. The hierarchical SOMs seem suited for robust and reliable seismic characterization workflows, with the scalogram attribute showing the greatest potential for advancing these methodologies.

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