Electrofacies Classification and Feasibility Study for Seismic Acoustic Inversion and Bayesian Classification in a Sandstone Reservoir, Campos Basin

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Abstract

This study focused on the electrofacies classification and feasibility assessment for seismic acoustic inversion in a sandstone reservoir located in the Campos Basin. In this work, we used nine wells and classified five electrofacies, including shale, carbonate, interlaminated, and two variations of sandstones, using a combination of two unsupervised-learning methods: hierarchical clustering and self-organising maps. The training step was performed with six well logs. Following the tests, we conducted a feasibility study using four facies, grouping the sandstone types, through Bayesian classification to determine the most probable electrofacies from the acoustic impedance well log. The total accuracy achieved was 69%, with a notable 81% accuracy for the sandstone facies. These findings contribute to more accurate reservoir modelling and effective decision-making in field development planning, offering valuable insights for improved reservoir understanding and resource estimation.

Introduction

The Campos Basin, which began its exploration in the 1960s, is a crucial area for oil and gas exploration and production in Brazil. Petrobras played a significant role in this exploration through their geophysical data acquisition campaigns and the drilling of the first exploratory well in shallow waters (Bruhn et al., 2003). Within this basin, the post-salt turbidite reservoirs in the Carapebus Formation are particularly noteworthy, as they have been the primary reservoirs for oil production in the country for a considerable period (Winter et al., 2007). However, these turbidite reservoirs are known for their complexity and heterogeneity (Bruhn et al., 2003). Therefore, comprehensive reservoir characterization studies are essential to understand the distribution of these sandstone reservoirs.

Well-log data analysis offers valuable insights into the subsurface lithological variations and assists in reservoir evaluation and characterization. Since manual facies classification can be laborious, one commonly employed technique is adopting a computer-assisted electrofacies classification. These approaches aim to automate the classification task within the reservoir zone based on machine-learning learning algorithms (Martins et al., 2022; Ali et al., 2023). These methods commonly differentiate lithological units in the well-log scale based on their well-log responses. They used several well logs, such as compressional slowness (DT), gamma-ray (GR), photoelectric factor (PEF), bulk density (DENS), neutron porosity (NEUT), and effective porosity (PHIE), to identify distinct electrofacies. To achieve accurate electrofacies classification, advanced data analysis techniques are often employed. Two widespread unsupervised machine-learning methods for electrofacies classification are hierarchical clustering and self-organising maps (SOM; Martins et al., 2022; Ali el al., 2023). Hierarchical clustering allows for the grouping of similar data points, while SOM reduces the dimensionality of the data by generating a 2D projection map (Everitt, 2011). These methods, combined with well-log interpretation and lithological descriptions, enable the identification and differentiation of electrofacies.

On the other hand, Bayesian classification is a supervised-learning method that has been successfully employed for upscaling facies classified in well-log scale to seismic (Avseth et al., 2005). Bayesian probability theory estimates the probability of a pattern of variables belonging to a specific class (Duda et al., 2001). Thus, the classification process results in the point-wise probability of facies, allowing uncertainty quantification. Furthermore, it supports introducing *a priori* probabilities for higher control of the geological knowledge during the classification process (Teixeira et al., 2017). The feasibility study for seismic acoustic inversion can use the Bayesian classification algorithm to analyse how the acoustic impedance can distinguish the facies (Fernandes e Lupinacci, 2022). This study is fundamental for understanding the potential for facies identification in the 3D seismic volume using the acoustic impedance volume provided by the seismic impedance inversion before spending resources to perform it.

In this study, we performed an electrofacies classification and feasibility study to characterise the acoustic impedance values and the lithological variations in the Carapebus Formation of the Campos Basin, Brazil. Hierarchical clustering and SOM algorithms were employed to divide the interest interval into five facies: shale, interlaminated, high-porous sandstone, medium-porous sandstone, and carbonatic. With the classified facies and the acoustic impedance logs, we achieved the feasibility study through the Bayesian classification. We evaluate qualitatively and quantitatively the results of our approach in two wells.

Method and Materials

This study used well-log data from nine wells drilled in the Carapebus Formation of the Campos Basin. Quality control procedures were implemented to ensure data accuracy, including removing abnormal spikes, merging data from different logging phases, interpolating short gap intervals, and sample rate verification. The following well logs were selected for electrofacies classification: compressional slowness (DT), gamma-ray (GR), photoelectric factor (PEF), bulk density (DENS), neutron porosity (NEUT), and calculated log effective porosity (PHIE_F) from bulk density and volume shale obtained through the neutron-density method. It is important to note that the GR logs were not used to calculate the effective porosity due to the presence of radioactivity in these sandstones, which is attributed to the presence of feldspar minerals in this formation (Fernandes et al., 2022).

For electrofacies classification, a total of five electrofacies were chosen based on the rocks description available to differentiate between shale, carbonate, interlaminated, and two categories of sandstones high and medium porous sandstones. The IPSOM Techlog's module was utilized, employing hierarchical clustering and self-organization maps (SOM) methods. The SOM method, developed by Kohonen in the 1970s, reduced the data dimensionality from multiple dimensions to a 3D representation, allowing for the generation of a 2D projection map for subsequent data grouping. The hierarchical clustering algorithm (complete) was then applied to perform the clustering, starting with each observation as a separate cluster and merging pairs until the user-defined number of clusters was reached. It is important to note that this method is probabilistic and generates different results with each classification. Multiple classifications were generated, and the one that best discriminated the classes based on the interpretation of each lithology in the well-log analysis was selected.

As part of the viability study, kernel density estimations (KDE) were constructed for each electrofacies using the acoustic impedance well-log. KDE is a non-parametric technique that estimates the probability density function that was chosen because in this type of estimation, the probability density function (PDF) tends to better capture the data compared to parametric approaches (Silverman, 1986). We employed the Scott's method (Scott, 1992) to estimate the bandwidth of the kernel. The KDEs were used in Bayesian classification to classify electrofacies based on the acoustic impedance values. Bayesian probability theory is a statistical approach that aims to estimate the probability of a pattern of variables belonging to a certain class (Duda et al., 2001). In this work was employed to determine the most probable occurrence of each electrofacies given the acoustic impedance.. This classification approach further enhanced the understanding of lithological variations and assisted in reservoir characterization.

Results and Discussions

After the classification process, we observed the results statistics for each electrofacies, which helped the interpretation and quality analysis. The mean and standard deviation of each electrofacies in the well logs used for the classification are presented in Table 1.

Table 1. Summary of the statistics of each electrofacies classified and the facies interpretation.

Facies Interpretated	Shale		Interlaminated		High Porous Sanstone		Medium Porous Sandstone		Carbonatic	
Electrofacies	1		2		3		4		5	
Colour										
Number of Neurons	30		27		27		12		4	
Well Logs	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
DENS	2.31	0.004	2.20	0.003	2.11	0.001	2.07	0.01	2.55	0.002
NEUT	39.3%	0.3%	38.8%	0.4%	33.7%	0.01%	40.6%	1.0%	20.5%	0.2%
PEF	3.82	0.06	3.49	0.08	2.82	0.05	3.16	0.09	4.05	0.01
DT	111.19	32.05	120.51	44.73	126.10	19.31	122.23	15.65	81.79	75.97
GR	98.47	160.94	89.02	48.02	77.07	82.57	110.89	59.85	74.99	19.57
PHIE_F	6.1%	0.2%	19.3%	0.3%	29.7%	0.04%	24.1%	0.2%	4.8%	0.1%

Electrofacies 1 exhibit relatively higher DENS (mean = 2.31) and lower effective porosity (mean PHIE_F = 6.1%). The neutron porosity (NEUT) is relatively high at 39.3%, indicating the presence of hydrogen-rich minerals such as hydrated clay minerals. Additionally, moderate values for DT, GR, and PEF are compatible with shaly formations. Therefore, Electrofacies 1 is interpreted as shale due to its distinctive well log characteristics.

Electrofacies 2 display a slightly lower DENS (mean = 2.20) compared to shale. They exhibit relatively higher effective porosity (mean PHIE_F = 19.3%) and slightly lower neutron porosity (NEUT = 38.8%) and PEF values (mean = 3.49%). This variation on well logs values with the increase of porosity indicates the alternating lithological layers within interlaminated formations of sandstones and shales in different proportions.

Electrofacies 3 is characterised by lower bulk density (mean = 2.11) and significantly higher effective porosity (mean PHIE_F = 29.7%). The relatively lower neutron porosity (NEUT = 33.7%) suggests a lower content of hydrogen-rich minerals and the lowest PEF mean of all electrofacies shows a higher quartz content. These values indicate sandstone facies.

Electrofacies 4 exhibits lower bulk density (mean = 2.07) and moderate porosity (mean PHIE_F = 24.1%). The relatively higher neutron porosity (NEUT = 40.6%) indicates an increased clay content, which is further supported by the relatively higher PEF values. This higher shale content explains the lower porosity mean observed in this electrofacies. Therefore, it represents a sandstone with intermediate porosity due to the higher shale content present.

Electrofacies 5 is characterised by the highest bulk density (mean = 2.55) and PEF values (mean = 4.05%), as well as the lowest porosity (mean PHIE_F = 4.8%) and gamma-ray (mean = 74%) compared to the other electrofacies. It is interpreted not as a lithology purely composed of limestone, but as a carbonate facies, more like marls or interlaminated facies with carbonate content.

The kernel density estimations (KDE) constructed for each electrofacies from the acoustic impedance well-log is shown in Figure 1. We observed a overlap for electrofacies 2 (interlaminated), ranging from 4000 to 7000 m/s* g/cm³, in relation to sandstones and shales. This is explained by the intercalation of the two lithologies in varying proportions, making their discretization solely based on acoustic impedance values challenging. So, it is expected that the Bayesian classification for this electrofacies will have a lower accuracy. However, a distinct peak is observed at 5800 m/s* g/cm³. The sandstone electrofacies exhibits the lowest values ranging from 3800 to 6800 m/s* g/cm³, with a prominent peak at 5000 m/s* g/cm³. The shale electrofacies spans from 4800 to 9000 m/s* g/cm³, with a peak at 6200 m/s* g/cm³. The carbonatic electrofacies has a limited occurrence from 5200 to 12000 m/s* g/cm³, being the only one with values above 9000 m/s* g/cm³.

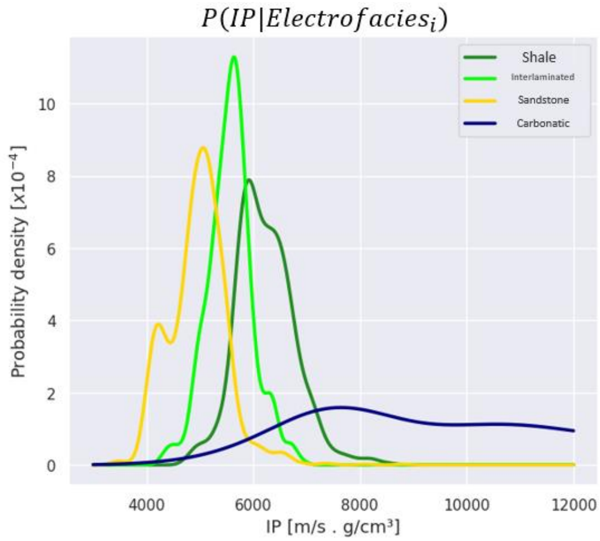

Figure 1. Kernel density estimations (KDE) were constructed for each electrofacies using the acoustic impedance well-log.

The probabilities *a priori* used for the Bayesian classification were selected based on the frequency of occurrence of each facies in the wells. We assigned *a prior* probabilities of 20% to shale, 30% to interlaminated, 40% to sandstones, and 10% to the carbonate facies. Afterwards, the Bayesian classification was conducted, resulting in an overall accuracy of 69%. To complement the quantitative analysis of accuracy, the confusion matrix was calculated for the Bayesian classification of the 9 wells classified (Figure 2).

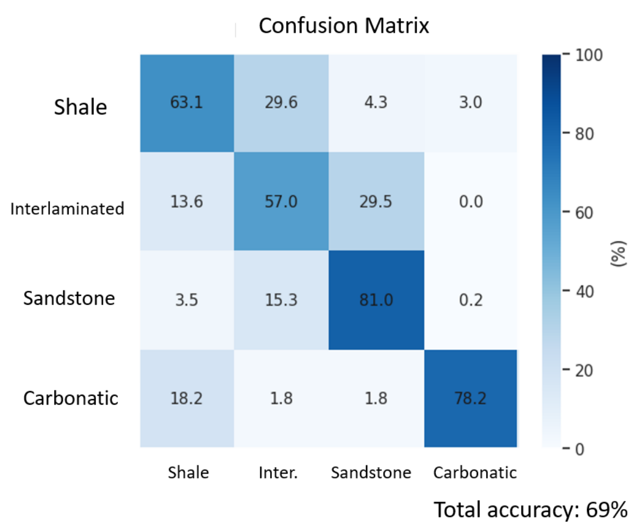

Figure 2. Confusion Matrix of the Bayesian Classification of the four main electrofacies.

Analysing the confusion matrix, we noticed a lowest accuracy rate (57%) for the interlaminated facies, which is expected considering the high overlap of acoustic impedance values. The shale facies had the second lowest accuracy rate (63%) being often confused with interlaminated and carbonate facies, suggesting the presence of shale content in these facies, even in the carbonate facies as mentioned in the explanation of electrofacies 5. The highest accuracy rate was achieved by the sandstone electrofacies (81%), which is the most important facies as it represents the reservoir facies in the study area.

Analysing well A (Figure 3), we observe accurate classification of thin layers across all lithologies. Interestingly, the interlaminated facies shows variations, at times classified as sandstone (near the upper reservoir) and other times as shale, found in the middle and upper sections of the well. Turning our attention to well B (Figure 4), we note a strong correlation in the classification, clearly indicating sandstone facies at the base and a predominant presence of interlaminated and shale facies towards the top. Notably, within the sandstone, relatively high impedances are observed, suggesting a higher complexity that remained unresolved by the unsupervised method.

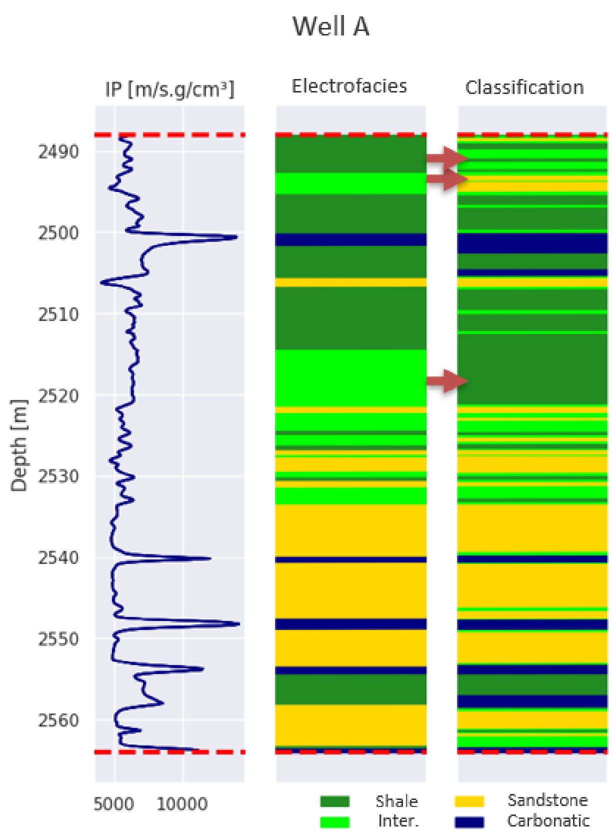

Figure 3. Visualisation of the classified facies through Bayesian classification in Well A, highlighting the good resolution in classifying thick and thin layers. The result presents a few confusions of interlaminated facies with sandstone and shale. The dotted lines indicate the upper and lower boundary of the target interval.

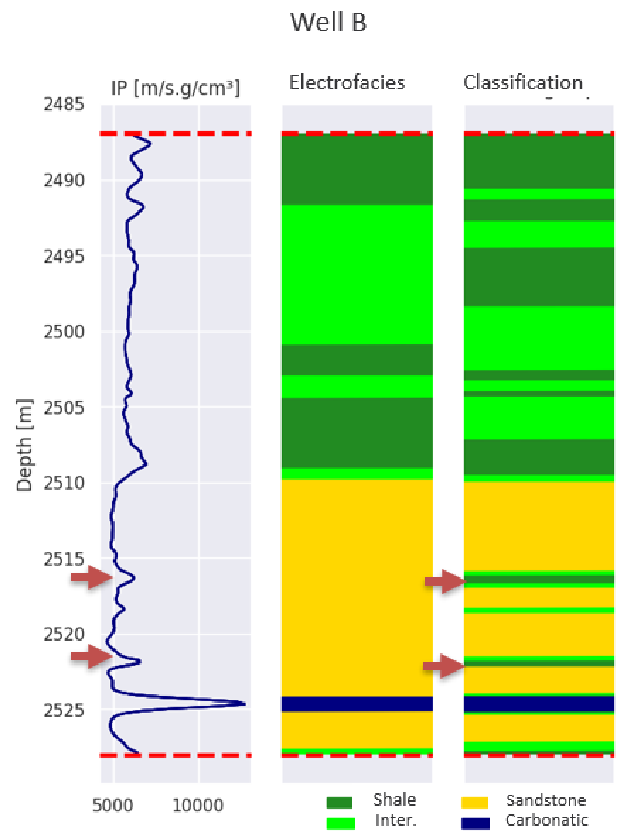

Figure 4. Bayesian classification results in Well B, showing the classification performed with excellent correlation, clearly indicating the presence of sandstone facies at the base and predominance of interlaminated and shale facies at the top. The arrows indicate relatively high impedances within the sandstone, indicating a higher complexity of these facies not classified by the unsupervised method. The dotted lines indicate the upper and lower boundary of the target interval.

Conclusions

The main conclusions are described bellow:

1- The electrofacies classification using well-log data and unsupervised method proved to be effective in differentiating between lithological units in the Carapebus Formation of the Campos Basin, Brazil.

2 - The chosen electrofacies (shale, carbonate, interlaminated, high porous sandstones, and medium porous sandstones) helps the reservoir characterization into lithological units that can be modelled using geological concepts.

3- The Bayesian classification approach, based on acoustic impedance values and *a prior* probabilities, yielded an overall accuracy of 69%.

4 - Among the electrofacies, the sandstone facies exhibited the highest accuracy rate of 81%, indicating its significance as the reservoir facies.

5 - The interlaminated facies showed the lowest accuracy rate of 57%, attributed to the high overlap of acoustic impedance values, making its classification more challenging.

6 -The shale facies had a 63% accuracy rate, often being confused with interlaminated and carbonate facies, suggesting the presence of shale content in these facies.

7 -The presence of relatively high impedances within the sandstone facies indicated a higher complexity that remained unresolved by the unsupervised method.

Overall, the electrofacies classification and Bayesian classification provided valuable insights into lithological variations and helped the reservoir characterization in the Carapebus Formation of this field.

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