Enhancing Unsupervised Machine Learning For Fluid Detection Through AVO Attribute Integration

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INTRODUCTION

Fluid identification from seismic data is particularly challenging in areas with heterogeneous facies, mixed lithologies, and variable signal-to-noise conditions. Traditional methods often use very few seismic attributes, which is particularly problematic in areas with high carbonate density or complex porosity distribution, as it becomes more difficult to separate fluid-induced amplitude changes from non-fluid-related attributes such as porosity or structural effects.The attributes derived from AVO make this distinction clearer.

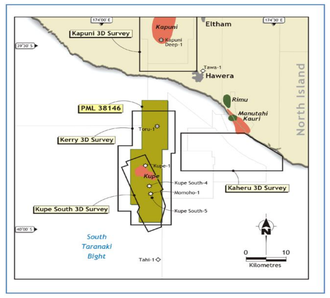


Figure 1. Location of my study area .

METHODOLOGY

What is the aim of:

Case 1 : To provide the best combination of global PCA methods as input to the machine learning methods I plan to implement

Case 2 : To see how the combination of AVO attributes and traditional seismic attributes can improve the outputs of machine learning methods.

Case 3 : With available well data, it offers a suitable test bed for evaluating fluid-lithology discrimination methods using AVO and rock-physics-consistent attributes. Manzar et al claims that Lambda Mu Rho is the best option for fluid detection (Manzar et al.2020).

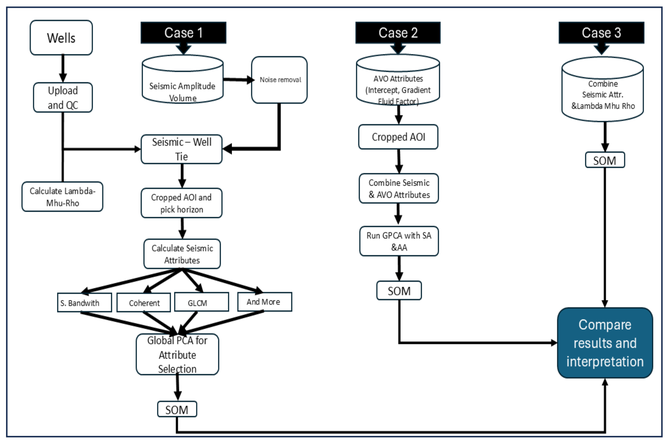
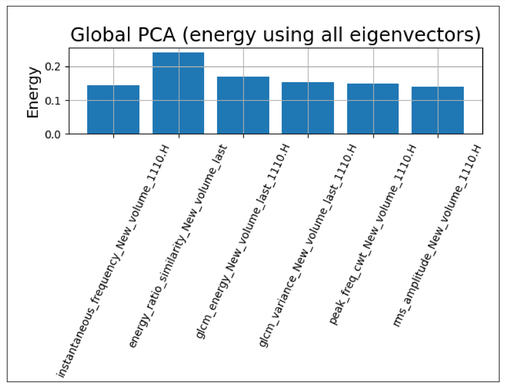


Figure 2. Workflow

DISCUSSION



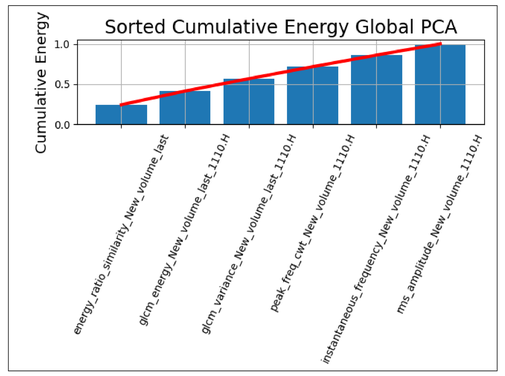
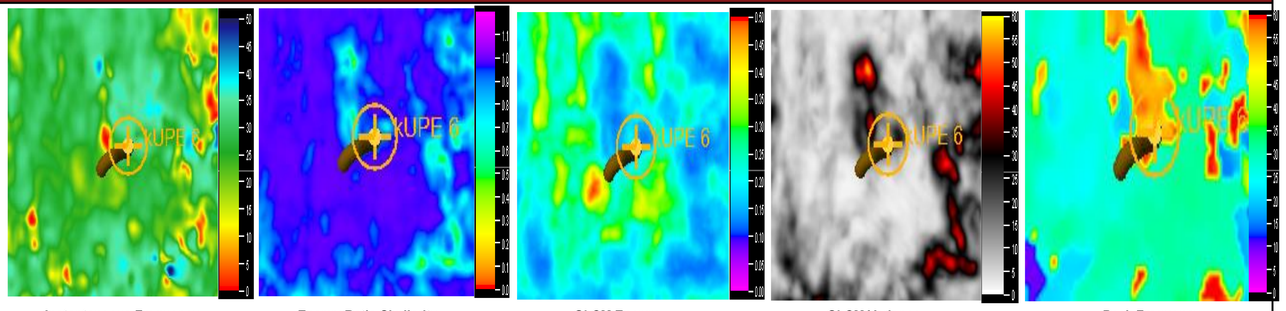


Figure 3. Results of Global PCA Methods



Instantaneous Frequency **Energy Ratio Similarity** **GLCM Energy** **GLCM Variance** **Peak Frequency**

Figure 4. Seismic attributes that they were used as an input with AVO attributes for SOM.

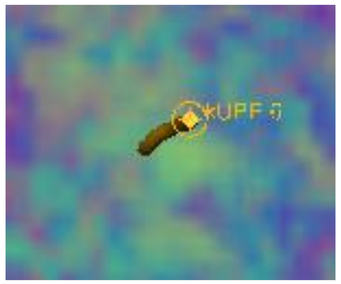


Figure 5. Som result by using seismic attributes

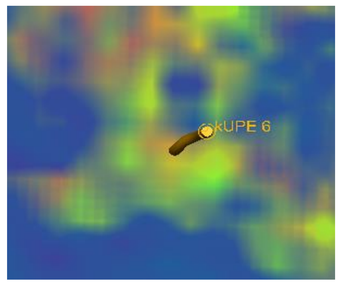


Figure 5. Som result by using seismic attributes and AVO attributes

CONCLUSIONS

The PCA and SOM results are presented along with the inputs derived from the generated attributes of the Kerry 3D seismic survey area. Although there are no large channel structures in the area, several smaller channel structures have been observed.

FUTURE WORK

This work will be further developed by using different attributes and other machine learning methods.

REFERENCES

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